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Competitive or Complementary: A Spatiotemporal Investigative Analysis into Austin's Shared Micromobility Modes.

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Competitive or Complementary: A Spatiotemporal Investigative Analysis into Austin's Shared Micromobility Modes.

by

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Dedication

To all,

who forget that light exists at the end of the dark tunnel..

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With this I can finally say that I am done with a key chapter of my life, gathering positivity from all the different kinds of experiences that were thrown at me, and ending with another question mark about what life will offer next. Whatever it is, will be worthwhile, just like my experience with graduate school.

Abstract

Competitive or Complementary: A Spatiotemporal Investigative Analysis into Austin's Shared Micromobility Modes.

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Supervisor: Ming Zhang

Shared micromobility has taken up US cities by storm over the past few years. Free-floating technology is the new age shared transportation innovation and has become widely popular amongst the younger-aged cohorts, giving users increased flexibility in terms of vehicle operation in comparison to the static station-based bike-sharing systems. This PR projects to find a better understanding of the three shared micromobility modes, thereby deducing whether the three modes are complementary or substitutive in nature. The research utilizes publicly available shared micromobility data from the City of Austin, to understand what the scenario exists in Austin, where all three micromobility modes are actively present. Applying temporal signatures, the research tries to identify whether variations occur for each type of shared micromobility mode across these attributes. It also applies hypothesis testing by employing methods like Analysis of Variances and Two- Sample T-Test of Means, to distinguish whether the three modes are statistically similar or dissimilar. Since the University of Texas at Austin is a significant entity for the city, the research tries to

investigate whether students and staff are crucial target user groups based on spatial visualizations of trips. The analysis concludes that all three micromobility modes are complementary and not substitutive, the reason being that users utilize these modes to travel for different purposes, across the similar or dissimilar geography, i.e. usage is subjective and depends on user preference. The only commonality observed between the three modes is the similarity towards deviating from their original paths assuming to conduct secondary activities. Variation of usage is seen across all three modes, which suggests that temporal signatures have significant effects on the usage. Key locations like south Downtown, the University of Texas at Austin, and the West Campus serve as major traffic hubs for all three modes. From these results, city officials can hypothesize potential station locations based on traffic generation and attraction of the free-floating modes and also come into potential partnerships with private operators to better expand the existing station-based bike-share system.

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Chapter 1: Introduction

The advancement of technology is rapidly changing the landscape around us. Transportation is witnessing a major paradigm shift because of this change. Technology induced transportation services include concepts of shared mobility in the form of ride-hailing, short time vehicle rental services (like mopeds, rental cars, bikes, scooters), and futuristic concepts of autonomous vehicles, which is altering the transportation fabric in a way never imagined. Shared Mobility includes a subset of mobility options known as “Shared Micromobility" which uses the concept of shared use of bicycles, scooters, or any other transportation mode with low speeds, to enable users to use a mode of transportation for a short term, based on the users’ needs (Shaheen & Cohen, 2019). Micromobility includes a diverse share of transportation modes and service models, to cater to the different needs of the users. These include dock-based bike-sharing (where a bicycle is picked up from a kiosk at a station and can be returned to any other station) and dockless bike-sharing and scooter-sharing (where a bicycle or a scooter can be picked up and returned at any location).

The concept of bike-sharing is not new. The world has observed many generations of bike-sharing, since the last 55 years. The advancement of information technology (IT) has taken bike-sharing to another level. The first IT generation bike-sharing system in the United States (US) was a publicly owned docked-bike sharing system in Washington DC, known as Smart Bike DC, in 2008, which later expanded and now is better known as Capital Bikeshare (Johnson, 2019; Shaheen, Cohen &Martin, 2013). With station-based bike-sharing systems or docked-based bike-sharing systems, a user only needs to check out a bike from any of the strategically placed stations and return it to any docking station within the same system. Cities are promoting the use of bike-sharing as cycling promotes a more sustainable mode of transportation and helps to reduce environmental, economic, and social costs (Wergin & Buehler, 2018). Bike-sharing systems make cycling convenient and attractive since the user does not have to own a private bicycle for use. At the same time, they can make one-way trips by simply dropping the bike off at a convenient location and return using a different transportation mode.

The recent three years have rapidly transformed the concept of shared biking, from a more static docked system to a more dynamic free-floating system. The free-floating system follows the concept that bicycles can be unlocked, used, and returned anywhere within a city, depending upon the user's origin and destination locations. In July 2017, the first dockless bike-sharing pilot program was launched in the US by the city of Seattle (Zamir et al, 2019). But the term "dockless" is not just limited to bike-sharing systems. Dockless vehicles, which include bicycles (both conventional and electric "e"-bikes) and scooters (mainly "e"-scooters), now exist side by side with the conventional station-based systems across many cities in the US. Currently, as recorded by the National Association of City Transportation Officials (NACTO), users in 28 cities in the US can access all three types of shared micromobility services as shown in Figure 1. It is the second-highest to a station-based bike-share system in the US (NACTO, 2018).

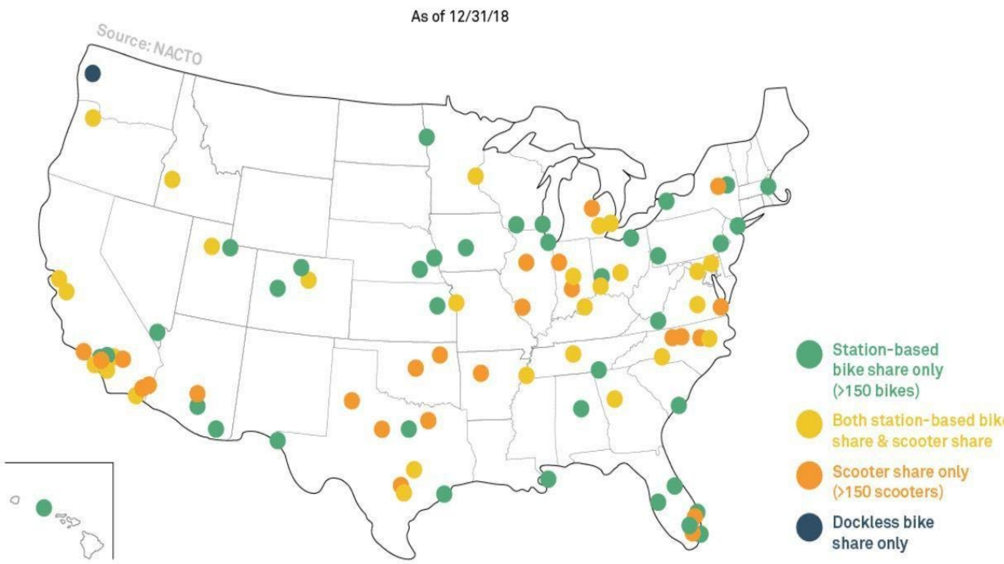

Figure 1: Micromobility implementing Cities in United States (Retrieved from: https://nacto.org/shared-micromobility-2018/)

Since the concept of bike-share has been prevalent for decades, the research associated in this field is vast. There are two folds in this research. The first fold includes studies that show how bike-share systems help in reducing congestion by expanding transportation options, provide increased environmental sustainability by decreasing greenhouse gas emissions, and induce major health benefits through increased physical activity (Shaheen et al, 2010). The second fold lies in dedicated research towards deducing user characteristics of station-based bike-share, user behavior, looking at impacts of the built environment on station locations, predicting bike-share usage, optimizing station locations, comprehending the best catchment area for bike-share stations, measuring bicycle environment and transit services to model transportation services as well incorporating weather and temporal variables in bike-share research (Wang & Lindsey, 2019; Alcorn & Jiao, 2019; Singhvi et al, 2015; Wang & Chen, 2020; Zhang et al, 2019;

Wang et al, 2016; Faghih-Imani et al, 2014). Dockless technology-induced mobility options are fairly new. Hence, research in this field is limited. But since dockless technology has made an impact in society and is co-existing with the conventional station-based bike-sharing systems, it is essential to understand the impacts that each of these shared mobility modes may have on each other. So, it is necessary to compare the types of services, to understand the user preferences and motivations for mode utilization.

Since 2010, NACTO has been keeping a record of the number of trips conducted using the conventional docked bike-sharing systems in the United States. Later when dockless bikes and e-scooters made their entry into the cityscapes, NACTO included these new concepts of shared mobility, referring to the three as "Shared Micro-mobility" (NACTO, 2018). NACTO recorded, in 2018, a whopping increase of 49 million micromobility trips, with dockless scooters entering the mobility market in 2017. Out of this increase, 38.5 million trips consisted of dockless scooters, comprising 45.8% of the total trips (NACTO, 2018). More than double the number of trips was undertaken in 2018 compared to 2017 as shown in Figure 2.

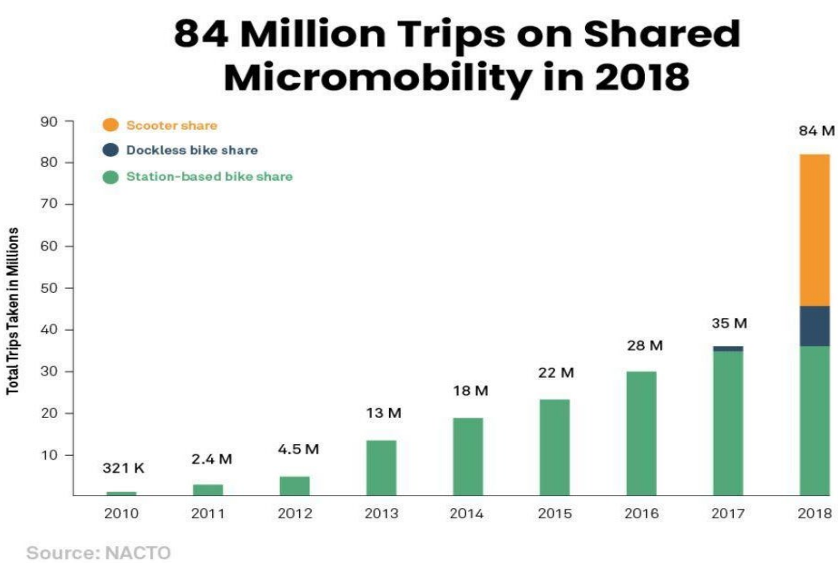

Figure 2: Micromobility Trips (2010-2018) (Retrieved from: https://nacto.org/shared-micromobility-2018/)

Looking at Figure 2, it is evident that with the influx of the two new micromobility modes of dockless bike and scooter share, station-based (docked) bike-sharing systems either lost a proportion of their users to dockless bikes and scooters (since the number of station-based bike trips did not increase significantly as compared to the previous years) or it can also be hypothesized that due to the increased availability of these new services, the user base overall increased. Now, if the first hypothesis is considered that station-based bike users shifted their loyalty to dockless mobility, then it can be inferred that maybe all the three mobility services are competitive i.e. one can be used instead of the other. Now considering the second hypothesis, that with the increase in availability in services, the user base has increased, it can signify that the three modes are complementary i.e. the user preference is different for each and that if the overall service increases or decreases, then the overall user base will increase or decrease respectively.

Even though there exists less research about the characteristics of dockless mobility users, conventional station-based bike-share users have been well established to be well educated (often having a college degree or higher), young adults (generally between the ages of 21 and 45), without children, usually in the middle and upper-income households living in urban environments with limited vehicle access (Shaheen and Cohen, 2019). Since dockless bicycles came before dockless scooters, researchers have identified factors like compact urban land use, higher levels of education, and employment, instigate users to cycle short distances (Li et al, 2018). A survey conducted by Seattle Department of Transportation, after employing a pilot project of free-floating bike-share, found that users were younger males, white, residing closer to the city center, likely to have or used a bike previously (Hirsch et al, 2019). Since dockless bicycles and scooters use similar technology and have other commonalities of vehicle size and personal travel demand, we can assume that similar results can be found for scooters as well (Jiao & Bai, 2020).

RESEARCH OBJECTIVE:

2018 saw an influx of dockless scooters in multiple cities across the United States, which a lot of cities were not prepared for, and received mixed reactions from citizens. Planners and transportation engineers had no time to assess their impact on existing infrastructure or city-provided services (McKenzie, 2020). But since these systems were privatized, many cities needed operators to provide standardized and open data, to understand the micromobility impacts, identify the gaps in the transportation networks, and monitor equitable service standards. As of December 2018, ten cities require operators to provide them with data, which includes attributes such as mobility trips, the status of the equipment, and service provider coverage (Shaheen and Cohen, 2019). This publicly available data can be utilized by researchers to understand the impact that each mode of transportation may have on each other, thereby understanding their user's preference and potentials that can help fix the gap between demand and supply, to bridge the gap in the transportation network.

The main question which comes into mind when utilizing trip data for analysis, is when and where do these micromobility trips take place? Visualizing micromobility trips based on time and space can help researchers, planners, and engineers understand user preferences. Statistically comparing these three modes will help to conclude whether the three modes are complementary or competitive. Hence this research will consider temporal variables (for example seasons, day of the week, time of the day) through a spatial resolution to understand how significantly similar or different each of these modes are from each other.

Research related to dockless bike-share and e-scooter share is limited. Either research has been conducted using a single-mode, looking at the trip data through temporal and spatial lenses, or two modes have been compared (for example docked-based bike-share vs. dockless bike-share, docked-based bike-share vs. dockless e-scooter share, dockless e-scooter share vs. other transportation modes) taking into consideration trip volumes. To the researcher's knowledge, only one analysis has been conducted considering all three modes, using trip data from Capital Bikeshare and other dockless operators in Washington DC. One of the main reasons for limited research is the unavailability of trip data across all modes.

Since the City of Austin provides both public-funded station-based bike-share data and dockless micromobility data through its Open Data Portal, this opportunity can be utilized to address the above-mentioned questions of "when and where" as well as identify gaps that may exist in this research.

RESEARCH QUESTIONS:

The main questions that this research will try to provide answers to are as follows:

1. Whether the three specific micromobility modes display variations taking into consideration:
    a. Temporal variables like seasons, time of the day, days of the week, using trip volume, average operation time, average trip distance.

b. Spatial distributions, thereby, visualizing trip data using ArcGIS across the City of Austin.

2. Whether three specific modes of micromobility: station-based bicycle sharing, dockless bicycle-sharing, and dockless e-scooter sharing display substitutional or complementary characteristics.
3. Consider if the usage of the three micromobility modes is influenced by The University of Texas at Austin? (Since a typical bicycle user characteristic points to well educated (often with a college or higher degree) younger adult (typically between 21 to 45 years)).
4. In what ways can the City of Austin learn from the results to implement a successful transportation network and bridge the gaps?

OUTCOMES:

This research concludes that the three micromobility modes are not like one another. Significant similarities may exist when compared to different temporal signatures within the same mode. For example, for a single mode, two weekdays may show similar results, but that does not conclude that they are statistically significant. Variations exist across the different days of the week, peak and off-peak times, months, and seasons. Overall, the only similarity that may show up when comparing these three modes is the average activity ratio. This signifies that even if the three micromobility modes are dissimilar, the only common factor may be the rate at which users deviate from their original path. This means that even if the users have a fixed destination, they do conduct other secondary activities along the trip. The difference in average operational time and reported trip distance varies across the three modes. Thereby, we can conclude that the three modes are utilized by users for different purposes, across similar geographies, thereby implying that the three modes are complementary and not competitive.

REPORT ORGANIZATION

The rest of the report is organized as follows:

- **Chapter 2** describes the context of the research, including the evolution of shared micromobility systems in the world, the technology involved in using these modes, the current scenario of micromobility in Austin, as well as previously conducted micromobility research.
- **Chapter 3** investigates previous spatiotemporal literature in connection to the three micromobility modes, the methods used along with the inferences and conclusions made by researchers.
- **Chapter 4** consists of a description of the data, data cleaning techniques involved to construct the datasets along with the methods used to analyze the data.
- **Chapter 5** provides detailed results of the quantitative analysis along with probable explanations. Charts are also included, to provide visual interpretations of the quantitative analysis.
- **Chapter 6** discusses recommendations along with probable policy implications.

Chapter 2: Background

Bike-sharing and scooter sharing services are rapidly growing across the U.S and are gaining wide popularity. By providing users the access to publicly-available shared transportation devices (bicycles and scooters) based on need, the system enables on-demand, low emission transportation modes that help to reduce congestion and pollution, while improving public health in urban areas (Lazarus et al, 2020). Conventional station-based bike-share systems have been around for the last five and half decades, where U.S cities have initiated publicly funded bike-sharing opportunities.

EVOLUTION OF SHARED MICROMOBILITY SYSTEMS (TRANSITION FROM PUBLIC BIKE-SHARING SYSTEMS TO FREE FLOATING BIKE-SHARING AND SCOOTER SHARING SYSTEMS):

The term "Shared Micro-mobility" as mentioned in the previous chapter, uses the idea of shared transportation modes and service models associated with low-speed vehicles, such as bicycles and scooters, enabling riders to access this short term service based on their needs (Shaheen & Cohen, 2019). Even though this term has evolved in the last half a decade or so, the concept of shared micromobility is not new. Bike-sharing developed over the last 50 years has undergone three generations based on their modes of operation. The first-generation bike-sharing systems included unlocked and painted bicycles, randomly scattered throughout urban areas. These bicycles could be picked up from anywhere and were free (Du, Deng & Liao, 2019). The first bike-share appeared in Amsterdam in The Netherlands in 1960, known as "White Bikes" because of their white-painted bodies. The program was stopped because of challenges faced in fleet management due to users taking them for private use, theft, and vandalism (Wu, 2019; Shen, Zhang & Zhao, 2018).

The second-generation bike-sharing programs were based on coin deposit systems. In the 1990s, users could pick up and return bicycles from specific locations within the city, with the introduction of docking stations for easy locking, payment, renting, and returning of bicycles (Deng & Liao, 2019, Shen, Zhang & Zhao, 2018). Copenhagen's "City Bikes" was the first large-scaled coin deposit bike-sharing system during this second phase (Deng & Liao,2019). In 1996, the twin cities of Minneapolis and St. Paul introduced North America's first coin deposit system called the "Yellow Bike Project" through a local health club's law firm (Shaheen et al, 2010). The coin deposit system of bike-sharing was overall unsuccessful, due to technological constraints, no fixed limit of bike usage, the anonymity of cash-paying users, and failed attempts to address theft (Shen, Zhang & Zhao, 2018).

The second generation gave away to the third phase of bike-sharing systems with the rapid advancement of Information Technology (IT). Here bike-sharing systems amalgamated with modern technologies like smartcards, electronic-enabled locking racks, cashless payments, dynamic pricing schemes at the docking stations (Deng & Liao, 2019, Shen, Zhang & Zhao, 2018). Users can unlock bikes at strategically located docking stations in the city, especially within the urban cores, and return them to the same or different station within the same system, by providing cashless payment as the cost for the usage time (Deng & Liao, 2019). This system along with cities' policy incentives gave way to a rapid expansion of the station-based bike-sharing systems across the world (Deng &

Liao, 2019). The majority of the station-based or docked bike-sharing systems in North America are publicly funded programs, often introduced as pilot programs, either operated through the government or public nonprofits. One of the barriers to the success of a bike-sharing service is the user's inaccessibility to docking stations. This has been overcome by the latest emerging generation of the bike-sharing systems which uses the same technology but with a dockless/free-floating system.

Dockless bikes were introduced in 2015, in countries like China, The Netherlands, and Singapore, with rapid growth being observed in the United States since 2017 (Deng & Liao, 2019; NACTO, 2019). In 2018, the US companies Lime and Bird became pioneers in introducing the concept of dockless shared electric "e-scooters" into America's urban environment, rejuvenating the micromobility fabric across the world (Ajao, 2019). Many American cities have become flooded with the sudden emergence of e-scooters, which run on the same concepts of the previous micromobility technology but are unhinged like the dockless bicycles and provide a more flexible and fun mode of transportation (Jiao & Bai, 2020).

TECHNOLOGY INVOLVED

Bike-sharing Systems:

Bike-sharing systems at present are of two types: fixed station-based bike-sharing systems, which have been popular across the world for decades, and the more recent free-floating type, unconstrained by docking stations. Information technology is deeply rooted in both these systems. The following discussion includes the technology used by each of these types of bike-sharing systems, and how riders access them to travel from one place to another.

Station/ Docked Based Bike-Sharing System (SBBS):

As mentioned earlier, strategically docking stations are located throughout the city, especially near the urban centers. Riders can unlock bicycles, by providing payment using cashless methods either at the docking stations or reserving a bicycle using mobile applications (apps). This kind of system may have membership passes ranging from annual, monthly, daily, or nonmembers can either purchase weekend passes or pay as they ride. Bicycles can be unlocked at the docking stations by verifying member accounts by using the same credit card used for signing up, via text message, or through mobile apps. Non-members who opt for the pay as you ride scheme can unlock the bicycles only at the docking stations for $1.00, and then the cost-per-minute to ride the vehicle varies on the city. The fee structure to use this service, and the membership features vary amongst cities. Once the user unlocks the bicycle, they are required to return the vehicle after their use to the same/different station within the same system. Some bike-sharing systems, for example, B Cycle at Domain, Austin, Texas, allows users to lock bikes anywhere within their service area for an extra fee of $3. Similarly, if users lock bicycles outside the service area, they get charged a penalty of $75, used as a retrieval fee to get back the bicycle (B Cycle LLC, 2019).

Dockless Bike-Sharing System (DBS):

In the case of dockless bicycles, users can rent bicycles using an app, which they would have to download on their phones. These systems mainly contain electric bicycles. Users need to create their profiles and store cash credits after which they can find bicycles that are located nearby for use. Riders can either go up to a bicycle if they see an available bicycle nearby or reserve a bicycle for use through the app. The reservation period is usually 30 minutes and the cost charge starts the moment the bicycle is reserved. Debit cards/credit cards/ stored cash credits can be used for riding these bicycles. Dockless bike-sharing systems can include an initial fee of $1 for unlocking the bicycles depending upon the operator and the city the user is in. Riders need to scan the Quick Response (QR) Code using their smartphones or manually put in the bicycle numbers to use this service. After using the bicycles, users must lock them within the service area. Dockless bike-sharing systems are usually based on the pay as you ride model, but membership passes, ranging from annual, monthly, and daily, as well as special passes for eligible riders with financial problems, may be available in certain cities. Normally, a rider is charged between $0.15 to $0.30 for each minute of travel depending on the city and operating area (McKenzie, 2020) But in case of passes, usually a fixed number of free minutes are provided to each pass per day, after which the user is incurred with normal charges, along with retrieval cost of $25, if the bicycles are left locked outside operation areas (Gutman, 2019). Many operators include both dockless bikes and e-scooters in a single app, so the features are similar for both.

Dockless E-Scooter Sharing (DSS):

E-scooters can only be operated if the app is downloaded on a smartphone, in which the users can sign up for their accounts for free. Using the app, users can find available e-scooters in their area, which they can either unlock for use or can reserve for use in the future. Reservations can only last for a span of 15 to 30 minutes depending upon the operator. Charging for the ride usually starts with the reservation being made. Clicking on the e-scooters on the App shows the number of miles the e-scooter can be used, and the amount of battery left for use. Users can pay using their credit cards/debit cards or can store cash credits for future use. The initial cost of unlocking a scooter is $1.00, after which each user must pay between $0.15 to $0.30 for each minute of travel depending on the city and operating area (McKenzie, 2020). Users utilize the same technology as dockless bicycles and scan the QR Code using their smartphone cameras or input in the e-scooter number, both of which are mentioned on the e-scooters, to unlock the vehicles. The mobile app also shows the users, locations where locking e-scooters are restricted, what recommended speed the user needs to use versus locations, where e-scooter parking is preferred, etc. If the user locks the e-scooter at a location outside of the service area, they are charged $25 as the retrieval cost. Depending upon the city, operators provide monthly passes for the public as well as special passes for eligible users with a financial burden. These monthly passes and special passes provide a fixed number of minutes of ride time for free every day, at a monthly nominal cost, after which additional riding time gets charged per minute. Other than the fixed free riding time, all normal charges are excluded in these passes, including retrieval costs if scooters are locked in areas outside of the service zone.

SHARED MICROMOBILITY IN AUSTIN:

The word “Shared Micromobility" isn't a new term for the City of Austin’s landscape. National Association of City Transportation Officials (NACTO) coins this term as “all shared-use fleet of small, fully and partially human-powered vehicles such as bikes, e-bikes, and scooters” and includes both docked and dockless categories of shared mobility (National Association of City Transportation Officials, 2018). The city of Austin refers to “Shared Micromobility " as “scooters, skateboards, or other compact devices designed for personal mobility which do not have a license plate” and excludes bike share (City of Austin, 2020). But for the reader’s reference, this report shall follow NACTO’s definition of Shared Micromobility and will be inclusive of all three types of mobility modes, be it station based/docked or dockless.

In 2013, the City of Austin introduced docked bike-sharing to its citizens, administered by the local 501 (c) (3) non-profit organization called Bike Share Austin (B Cycle LLC, 2016). B Cycle runs on funding provided through government grants, private sponsorships/advertising agreements along with the revenue generated via user fee (Alcorn and Jiao, 2019). As of Dec 2019, Austin B Cycle recorded 1.22 million bike trips, equating to an approximate annual ridership of 240,000 as reported by the Austin Transportation Department through their Open Data Portal (Austin Transportation Department, 2019). Bike-sharing enthusiasts have different opportunities to access this mobility option, either through membership, daily passes, or pay as you go. B Cycle also offers student memberships for the students and staff at local universities like The University of Texas at Austin and Huston-Tillotson University. At present, Austin B Cycle has 75 stations distributed across Austin mainly around Downtown, The University of Texas at Austin, and besides the Colorado Riverfront.

In 2018, the City of Austin integrated more shared micromobility services into the city's landscape through their dockless bike-share and scooter-share pilot program. The City of Austin was in talks with the community through public forums, about introducing a pilot program for dockless mobility options, namely bike-sharing, during February 2018 (Transportation Department, City of Austin, 2018). But before the pilot program could start, two e-scooter companies, Bird and Lime had launched themselves in Austin. Amongst this chaos, the City of Austin, decided to include e-scooters as a part of the dockless mobility pilot program and enforced rules and regulations for them (Austin Transportation Department, 2018). To control the supply of e-scooters in Austin, such that riders maintain rules and regulations, licenses became mandatory for the companies who were launching these mobility options. E-scooter companies are licensed to operate in Austin's Downtown Coordination Zone (mainly the Central Business District or CBD), which serves as the main site for the pilot program. Additional licenses are given to operators to provide extra units in areas that do not fall within the pilot area (City of Austin, 2020). Till March 2020, there were 5 e-scooter operators in Austin: Bird, JUMP, Lime, Lyft, and Spin, with a total of 15,350 scooters available to the public as mentioned in the City of Austin's "Shared Mobility Services" website. To keep Austin running safely, the City of Austin has also laid laws and regulations applicable to micromobility (City of Austin, 2020).

Simultaneous to the e-scooter revolution in Austin, in 2018, the City of Austin introduced its dockless bike-sharing pilot program, restricted within Austin's Downtown Coordination Zone, from May 1st, 2018, for a 6-month trial period, where it confined each operator's fleet by 500 vehicles. Additional licenses could be obtained to operators that provided extra units outside the pilot area. In March 2020, there were 2 operators in the City of Austin: JUMP and Wheels, with a total of 2000 e-bikes, that could be used by the citizens. As of March 2020, the City of Austin has observed an increased number of users opting to use dockless mobility and has recorded an estimate of 9.27 million e-bikes and e-scooter trips (Austin Transportation Department, 2020).

PREVIOUS RESEARCH:

Since bike-share has been prevalent over the last 5 decades or so, consistent research exists based on this mode, pre and post IT revolution. Station-based bike share has existed for the maximum time span in comparison to the dockless kind, hence most of the related research has been conducted using this system. Research associated has been conducted in two directions. Firstly, looking through the lens of sustainability, studies have explained how bike-sharing systems can help the environment in reducing congestion by providing alternate means of transportation options, decreasing pollution by lowering greenhouse gas emissions as well as stimulating major health benefits through increased physical activity of the users (Shaheen et al, 2010). The second set of studies is devoted towards understanding the characteristics of station-based bike-share riders, user behavior, and how built environments can impact station locations (Wang & Lindsey, 2019; Alcorn & Jiao, 2019). Researchers have based their research models to investigate the prediction of bike share usage, optimize station locations, as well as comprehend the best catchment area used for analyzing bike-share stations, and measure cycling environment and transit services to understand transportation services (Singhvi et al, 2015; Wang & Chen, 2020; Zhang et al, 2019; Wang et al, 2016). Faghih-Imani et al (2014) have also incorporated weather and temporal variables in analyzing bike-share systems. The majority of the information used in these above experiments did not use real-time data. This is because IT-based bike-share systems are just over a decade old and have recently started making real-time data available to researchers through their respective Application Programming Interface (API) systems.

Free Floating technology-induced bike-sharing systems have evolved rapidly since 2016 due to their flexibility and convenience (Younes et al, 2020). But research in this field is limited, due to the initial unavailability of data from the private operators. As of 2018, 28 and 25 US cities observed dockless bicycles and e-scooters being operated respectively (National Association of City Transportation Officials, 2018). Since previously, a lot of research had been conducted for bike-share, dockless bike-share systems showed a correlation to a lot of similar indicators to station-based bike-share. Shen et al (2018) identified the existence of compact land use, accessibility to public transportation, accommodating cycling environment, and infrastructure promoted the increased usage of dockless bicycles in Singapore. At the same time, high temperatures and rainfall harmed bicycle usage (Shen et al, 2018). Li et al (2019) investigated and compared private bicycles, public bike-sharing (station-based), and free-floating bicycle share, and concluded that dockless bicycles were mostly used by young, low-income individuals and students compared to station-based bike-share in Kunming, China. In Jiangsu, China, Li et al (2018) concluded that dockless bike-share was mostly used for short-distance travel, especially as commuting modes for going to work or to schools, where the period of travel coincided with peak hour travel in urban areas. Mooney et al (2019) conducted a study in Seattle which pointed towards the inequity in dockless bike-share, similar to station-based bike-sharing systems, where the fleet was more favorable in socio-economically advantaged areas especially near the urban cores of cities. A survey conducted by Seattle Department of Transportation, after employing a pilot project of free-floating bike-share, found that users were younger males, white, residing closer to the city center, likely to have or used a bike previously (Hirsch et al, 2019).

McKenzie (2020) stated that dockless e-scooters represent a novel solution to the first and last mile problem in transportation, providing low cost-effective alternative transportation options in urban areas. The majority of the limited research includes the emphasis of e-scooters on the social impacts of the environment, parking positions, safety factors, and optimizing fleet distribution (McKenzie, 2019). Jiao & Bai (2020) concluded from their results of e-scooter research in Austin, Texas, that these systems were positively correlated to areas of high population density, with higher education, but negatively correlated to young residents. Increased e-scooter use was positively impacted by the presence of transit stations, better street connectivity, compact land use especially near the urban cores of Austin. An e-scooter study in Washington DC concluded that both dockless bicycles and e-scooters had shorter trip times, like registered members of DC's station based-bike sharing system, with no significant difference between the weekdays and weekends (Zamir et al, 2019). During a survey conducted by Portland Bureau of Transportation in 2018 for the e-scooter pilot program, positive notions supporting e-scooter usage came from minority communities, low-income households, and younger adults, saying that electric scooters were much more convenient than owning a car (Shaheen et al, 2019). Apart from the research mentioned above, many researchers have conducted spatiotemporal analysis studies, to understand the mode usage, taking into consideration temporal attributes and spatial resolution, some of which are discussed in the next chapter.

Chapter 3: Literature Study

Many scholars utilize spatiotemporal approaches in their respective research related to mobility/micromobility modes. With this research, authors have either compared a single mode or a maximum of two modes. But limited research exists in all three micromobility options. This section will highlight how researchers utilize the various aspects of temporal and spatial dimensions, on different kinds of data, methods, to find solutions for their research questions. The section below highlights information that can be relevant in later portions of this research.

Comparing the Temporal Determinants of Dockless Scooter-Share and Station Based Bike Share in Washington DC:

In this article, Younes et al (2020) compare DSS and SBBS modes, analyzing and evaluating how determinants like weather, gasoline prices, local events, day of the week, or time of the day have an effect on the hourly trip volume and the median duration of trips. A six-month data is selected from the major e-scooter share operators through their APIs and from Capital Bikeshare DC for analysis, utilizing a negative binomial regression model. Results observed in the research are as follows:

- Weather: Earlier established by previous authors that warm weather and better visibility has a positive impact on the increase in hourly trips, whereas precipitation, wind speed, and humidity have a negative impact. Casual SBBS riders are more susceptible to weather condition changes, in comparison to DSS, as free-floating modes provide the flexibility of leaving the modes at any permitted area and the reduced physical effort connected to it. The change of weather is not as effective on SBBS members, in comparison to casual riders, because of the habitual behavior of SBBS members in terms of travel which leads to a less expensive price structure.

- Time of the Day: Afternoon peak (3 PM to 6 PM) is the highest or second-highest, overall, in terms of trip count. For DSS, maximum trips occur during the midday (12 PM to 3 PM), compared to the afternoon peak. For SBBS, both midday and morning peaks (6 AM to 9 AM) are significantly like the afternoon peaks in terms of trip activity.
- For DSS and casual SBBS riders, peak activity occurs during Saturday, followed by Sunday. Also, for DSS, no significant difference exists between Fridays and Sundays in terms of trip counts. SBBS members show higher trip activity during the week in comparison to the weekend, with Monday accounting for the least number of significant trips.

COMPARATIVE ANALYSIS OF USER BEHAVIOR OF DOCK-BASED VS. DOCKLESS BIKE SHARE AND SCOOTER SHARE IN WASHINGTON, D.C:

The research by Zamir et al (2019), tries to show the comparative analysis of user behavior for the three micromobility modes, by identifying similarities and dissimilarities. The research uses descriptive statistics, logistic regression, and random forest modeling approach. They utilize data directly obtained from the dockless mobility operators and Capital Bike Share. The first part of the analysis uses descriptive statistical results based on trip volume occurring throughout the week and during different periods of the day. The second portion of the analysis talks about how spatially dispersed trips take place in Washington DC. The research concludes the following results:

- Day of the week: SBBS members conduct their trips during the weekdays, with a peak on Thursdays, which decreases during the weekends. DBS shows consistency throughout the week, without a drastic increase or decrease taking place.
- Time of the day: SBBS member trips show peaks occurring between 8 AM to 9 AM and 5 PM to 6 PM, along with a smaller peak in the midday (around 12 PM to 1 PM). DSS's peak hours occur between 8 AM to 10 AM and 5 PM to 7 PM (an hour longer than normal peak hours), along with an afternoon peak (between 12 PM to 1 PM).
- DSS's similar morning peak time corresponds with DBS (from 8 to 9 AM), along with an afternoon peak which starts at noon extending to 5 PM, highest record at 3 PM. For the weekend, peaks occur around noon for SBBS members, 1 PM for DSS, and 3 PM for SBBS casual riders and DBS.
- Trip Duration: Time spent on the three modes differ between the dockless and station-based users. SBBS members make short trips, within 15 mins, trips occurring between 5 AM to 9 AM, and after 8 PM. Similar trend is also seen in the case of the other free-floating modes, having a median trip duration of 10 mins.
- Spatial Distribution: Spatial distribution of trips is different for all three modes. DSS and SBBS Member trips originate from residential neighborhoods and end at mixed-use, in the morning. DBS trips concentrate within downtown and in employment areas.

The study suggests that free-floating systems complement the SBBS, but behavior-wise differs between the two when comparing it to SBBS.

DOCKED VS. DOCKLESS BIKE SHARING: CONTRASTING SPATIOTEMPORAL PATTERNS:

Grant McKenzie (2018) investigates docked and dockless bike share in Washington DC, to understand the working of dockless bike-share as well and analyze the difference that may exist between free-floating bike share and SBBS systems. McKenzie uses the data obtained from Capital Bikeshare and from Lime Bike with which he analyzes trip volume for the different periods across the days of the week, spatial locations of trip occurring, and network patterns for both the modes. He uses data mining and ArcGIS (Voronoi tessellations to locate trips within them) to obtain the following results:

- Temporal Differences: The mean time spent on both modes is 18 minutes, where the median trip time for SBBS is 11 minutes in comparison to the 5 minutes for DBS. The author reasons that increased timing for SBBS can be accounted for the need of finding docking stations, unlike DBS, where the vehicles can be left anywhere. Distinct morning peak occurs at 8 AM for SBBS, DBS trips volumes are more towards early and late afternoons. Both bike-share shows peaks at 5 PM on weekdays. This study suggests that based on temporal patterns, SBBS is mostly used for commuting for work than DBS.
- Spatial and Network Patterns: The study shows that SBBS trips concentrate in the urban core (central business district (CBD)) compared to DBS, which occurs more outside the City's core.

The study concludes that both modes vary from each other on the basis that the users utilize the service differently.

INCORPORATING THE IMPACT OF SPATIO-TEMPORAL INTERACTIONS ON BICYCLE SHARING SYSTEM DEMAND: A CASE STUDY OF NEW YORK CITI BIKE SYSTEM:

Faghih-Imani and Eluru (2016) et al's study incorporated spatial and temporal effects, to model bicycle demands for New York's public-funded bike share. Researchers use data provided by the operator. Peak times, weekdays vs. weekend, and weather variables like temperature and precipitation are utilized in this study through spatial error and lag models, along with the built environment and lag variables. The researchers observed the following spatiotemporal results:

- Time and weather variables: The study demonstrates that different times of the day have a significant effect on the arrivals and departures of bike-share users. Results indicate that users utilize this mode more between 16:00 and 20:00, compared to other times of the day. SBBS members made more trips during the weekdays compared to nonmembers who biked more during the weekends. The study assumes the temporary passes used are mostly for recreational purposes. Looking at weather variables, the study highlights that users were less likely to use service due to rain and high humidity conditions, whereas temperature does not have any effect on the usage of trip volume.

UNDERSTANDING THE SHARED E-SCOOTER TRAVELS IN AUSTIN, TX:

Jiao and Bai (2020) conduct DSS analysis using data provided by the City of Austin's Open Data Portal, to understand the distribution of e-scooter trips, and their relationship with the built environment. The researchers employ descriptive analysis on the e-scooter data, conduct hotspot analysis, and employ Anselin Local Moran's I, to investigate the clustering of e-scooter data occurring in the city. Negative Binomial modeling is used to understand the relationship between trip usage and built environment factors. The results of this research observed are as follows:

- Temporal Analysis: Average trip duration and distance is 7.55 minutes and 0.77 miles, respectively. The difference in the pattern for daily ridership is observed comparing weekdays and weekends. Weekdays have average users traveling 0.81 miles, taking 8.62 minutes, whereas on the weekend's users travel an average distance of 0.71 miles for 6.82 minutes. For weekdays, peaks occur at noon and in the evening around 5 PM, with trips ranging between the time frames of 8 AM and 8 PM. During weekends, trips start to take place after 11 AM, with a gradual increase during the afternoon till evening. After 8 PM, for both weekdays and weekends, e-scooter usage decreases significantly.
- Spatial Analysis: Through hotspot analysis, it was seen that clusters exist in two areas. Firstly, at the CBD, and secondly, in and around The University of Texas at Austin, with most outflow trips occurring downtown, with destinations located

outside. The University of Texas at Austin is observed as a major inflow hub with incoming trips from nearby residential areas.

URBAN MOBILITY IN THE SHARING ECONOMY: A SPATIOTEMPORAL COMPARISON OF SHARED MOBILITY SERVICES:

Grant McKenzie (2020) compares dockless mobility modes (e-scooters and electric bikes) with ride-hailing, utilizing data from Dockless Operator's API, along with ride-hailing movement data from Uber for Washington DC. The study asked important questions related to the existence of differences in the usage of the micromobility modes, temporally and spatially, to help understand the spatial dominance. The similarities are visually portrayed using graphs and statistically measured, using Watson's nonparametric two-sample test of homogeneity, as well as Cosine Similarity, based on trip volumes. The researcher uses Kernel Density in ArcGIS to preliminary understand the spatial distribution of the micromobility modes. Earth Mover's Distance is used to compute the spatial similarity between the modes. The results of this research are mentioned below:

- Temporal Activity: DBS is identified as the most dissimilar when in comparison to DSS, with results rejecting the null hypothesis. Scooter share operators also show dissimilarities when compared with each other, which is reflected through its different travel distance and operational time. The difference between the DBS and DSS is explained by suggesting that these bikes require users to pedal to travel. This can account for the difference in modal preference and is associated with longer trips.

- Spatial Activity: Using the above methods, it is seen one of the DSS operators show the greatest dissimilarity spatially when compared with DSS and DBS, in terms of spatial distribution. DBS results as the mode with the greatest similarity when compared with the other DSS, when in pairs.

The research concludes that even though different operators provide service over the same temporal and spatial regions, each mode shows differences amongst each other, in terms of trip duration and spatiotemporal signatures.

Micromobility evolution and expansion: Understanding how docked and dockless bike sharing models complement and compete – A case study of San Francisco

Lazarus et al (2020) conduct this research to understand how docked and dockless bike share can compete or complement each other through rider's travel behavior, employing three distinct approaches: travel behavior analysis, discrete choice analysis, and geospatial suitability utilizing Spatial-Temporal Economic Physiological Social (STEPS) to Transportation Equity framework. The research utilizes two datasets that the author received from Ford Go Bike (docked) and Jump (Dockless) for the City of San Francisco, to conduct their analysis, for February 2018. The results of the spatiotemporal aspect of this research observed are as follows:

- Travel Behavior: Around 32-33 percent of the dockless and nonmember docked bike users travel during the morning, compared to a higher percentage of docked bike share members. Morning demand concentrates in dense employment centers. But distribution wise, there exists a difference where origins of SBBS trips concentrate near railway stations, free-floating bike share trips are distributed across neighborhoods outside the CBD. During the evening hours, the destinations for both types of trips are opposite as well, where DBS trips end in neighborhoods outside the CBD, SBBS trips end near railway stations. DBS trips are longer in distance and duration in comparison to the SBBS trips. The study also assumed that longer trips for DBS result from trips being more recreational.

The study concludes that both modes complement each other. In the case of SBBS, trips are shorter, originating/terminating at railway stations, whereas for DBS, its longer and heavily operates around low residential neighborhoods outside the CBD.

ANALYSIS OF E-SCOOTER TRIPS AND THEIR TEMPORAL USAGE PATTERNS:

Mathew et al (2019) analyze e-scooter data in Indianapolis, for three months, provided by the City of Indianapolis, to analyze usage patterns based on temporal signage. The research utilizes descriptive statistics to understand the variations that take place during different times of the day and week. The results are mentioned as follows:

- Peak usage periods occur between 4 PM and 9 PM on weekdays, and between 2 PM and 7 PM on weekends. These peak times are different from the conventional morning and evening peak times. Usage starts mostly after 11 AM on all days and goes on till 9 PM. Due to the low morning usage, researchers conclude with the indication that maybe scooters are not a significant choice for the morning commute.

Spatiotemporal comparative analysis of scooter-share and bike-share usage patterns in Washington DC

Grant McKenzie (2019) in his research tries to identify and compare the usage patterns of dockless scooters and publicly-funded bike-sharing services, utilizing spatial and temporal signage. Researchers obtain data for both types of mobility to understand whether variations exist between the two types over the day as well as across spatial distribution. McKenzie uses data mining techniques and trip volume using bar graphs for visual presentation. Statistical similarity or dissimilarity is found using Cosine Similarity, along with Watson's Two-Sample Test for Homogeneity. Spatially trips are distributed across the city to identify the land use for the origins and destinations for each trip. To understand the differences in trip volumes across weekdays and weekends, trips are intersected with Traffic Analysis Zones (TAZ) and Global Moran's I is used. To compare the two modes further, Earth Mover's Distance is employed to understand whether the modes were statistically significant. The results of the research are mentioned as follows:

- Temporal Analysis: To understand whether similarity exists between scooter usage within the day of the week, it was seen that Tuesday and Thursdays show the most similarity in trips, followed by Saturday and Sunday, and least similar usage between mid-weekdays and weekend. In comparing the two modes, casual bike-share users are more like scooter-share users, than bike share members. Statistically, significant differences exist between bike share and scooter share looking through temporal patterns. Scooter share trips fall more towards casual bike share, signifying that its mostly used for recreational purposes, and reflects less towards standard commuting patterns.

- Spatial Analysis: Scooter usage distribution varies between weekdays and weekends. Observations suggest that weekday trips mostly concentrate in the downtown areas, whereas weekend trips are more dispersed near locations of recreational value. Comparing the two modes, it is seen that both bike-share users (members and casual members) show significant similarity across spatial dimensions, and least similarity between casual bike share usage and scooter usage, signifying that even though temporally casual bike-share users show similarity with e-scooter users, in the spatial dimension, they are quite different.

The main conclusion that the researchers establish is the fact that both modes are used for different purposes and complementary to one another.

A MODEL FRAMEWORK FOR DISCOVERING THE SPATIOTEMPORAL USAGE PATTERNS OF PUBLIC FREE-FLOATING BIKE-SHARING SYSTEM:

Du, Deng & Liao's article (2018) presents a model framework used to explore spatiotemporal patterns for DBS in Shanghai, China. The researchers utilize probability fitting, Random Forest cluster-based time-space analysis, and formed a visualization tool, using travel distance and time as variables. Researchers use a month of global positioning system (GPS) bike data for the study. Results obtained are mentioned as follows:

- Maximum trips with increased trip time and trip distance occur between the time frames of 8:30 AM to 9:30 AM and 4:30 PM to 5:30 PM (peak times).

- The highest usage influencing factors are residential areas, population, parks, and green spaces. A portion of the off-peak trips is recreational as it is associated with green spaces and parks.

UNRAVEL THE LANDSCAPE AND PULSES OF CYCLING ACTIVITIES FROM A DOCKLESS BIKE SHARING SYSTEM:

Xu et al (2019) use data mining on a four-month data obtained from bike-sharing operators in Singapore, to analyze the causes and variation of rider behavior utilizing temporal attributes in their study. Researchers use Eigen decomposition to understand bike share usage across the city, by considering bike-share demands on an hour to hour basis and comparing trip arrival and departure during weekdays and weekends. The results of their research are as follows:

- Temporal patterns: Researchers observed that weekdays show similar temporal patterns for bike share usage. Peak hours are seen between 8 AM and 9 AM and between 7 PM and 8 PM, with an increase in trips during the evening times for weekdays. For weekends, the patterns differ with the first peak time reaching around noon and second peak around 6 PM, with higher usage during the evenings.
- Spatial Distribution: It is observed during weekdays that most of the locations around rail stations receive equal distributions of trips, especially during the mornings. For weekends, the bicycle stations near the rail transit stations at the CBD receive higher attractions of bike share, around the afternoon and evenings, signifying users have recreational interests for those trips like shopping, dining, etc.

On weekend mornings, rail stations located in residential areas receive more bike-share traffic.

This study helps to understand how bike share serves as the first and last-mile option in the city.

INVESTIGATING THE SPATIOTEMPORAL DYNAMICS OF URBAN VITALITY USING BICYCLE-SHARING DATA:

Zeng et al (2020) analyze one week's bike share data from Beijing, China to investigate the cities and regions' interactions of bike-share riders at two spatial resolutions. The research used Analysis of Variance Test (ANOVA) and Wilcoxon Signed Rank test to compare the temporal variations across the week. Research also uses spatial autocorrelation and hotspot analysis to understand the spatial features across different periods. The results of the analysis are as follows:

- Temporal Variation of Bike Share Analysis: Research states that during weekdays, daily variation was almost similar, and weekends had higher trips compared to weekdays. The Wilcoxon Rank Test further proved that temporal variation was almost similar during the different days of the week and varied significantly with Saturdays and Sundays. Two distinct peak times are observed throughout the weekdays, between 8 AM and 9 AM and 6 PM to & 7 PM, which is not observed in the case of Saturdays or Sundays.
- Spatial Variation of Bike-share Analysis: Based on Moran's Index of spatial distribution, morning, evening, and night hours shows that clusters exist in certain

areas, whereas midday time shows that the trips were generated randomly. Morning clusters show the strongest intensity compared to the evening. Based on hotspot analysis, high and low clusters are observed during different periods. Both high and low clusters are observed during the morning hours, but only high values are observed during the evening and night.

Most of the research mentioned above which deals in comparing at least two modes, concludes that these micromobility modes are not competition. They have their characteristics when it comes to trips taking place across different periods. The difference in operation time and distance suggests that the modes are used for different purposes. Operational time and distance traveled varies across the geography, and hence differences in values are observed across different cities. Similarities in usage are observed while comparing within the same mode, namely on distinct days. Similarly, different peak times are observed across the three modes, which may or may not coincide with the typical conventional peak times, across weekdays and weekends. Different cities have captured differences in trip volume across the different days of the week, with an overall increase over the weekends, but have not gone in-depth related to the differences in time spent utilizing the mode and well as distances covered.

Chapter 4: Data and Methodology

DATA

To better understand the usage of the different urban mobility services provided in the City of Austin, this study gathers data from the Austin Transportation Department, for Station Based Bike Share (SBBS) and free-floating bicycle and e-scooter share. SBBS, better known as in Austin as Austin B Cycle, is a publicly subsidized bike-sharing service started in the year 2013 (B Cycle, LLC, 2016). Austin Transportation Department publishes Austin B Cycle Data on their Open Data Portal that has become publicly available since January 23, 2017, and is updated regularly (Austin Transportation Department, 2019). In 2018, the City of Austin has integrated shared micromobility services through their dockless bicycles and e-scooters pilot program into the city's landscape and regularly publishes a dockless mobility data on Open Data Portal since January 24, 2019, for its citizens, thereby providing complete transparency of the services (Transportation Department, City of Austin, 2018; City of Austin Transportation Department, 2019; City of Austin, 2019).

Since the City of Austin provides trip data through its data portal, it serves as the main data source for this research. This study gathers 8 months of docked and dockless vehicle data (July 2018 to Feb 2019) published by the Austin Transportation Department on the Open Data Portal of the City of Austin. The main reason why the period from July 2018 to Feb 2019 is chosen for this study is that, on 12th April 2019, Austin Transportation Department has decided that in order maintain the anonymity of its users, dockless mobility trips henceforth will be aggregated to Census Tracts for both Trip Origin and Trip

Destination (Austin Transportation Department, 2020). Before this, coordinates of Trip Origin and Trip Destination locations were given up to three decimal points for both latitudes and longitudes, which City of Austin's technology office had aggregated the Origin-Destination coordinates to a hexagonal grid of 0.023 square miles and 500ft edge length (Jiao and Bai, 2020).

SBBS/Austin B Cycle Data (Docked Bike-Sharing System)

SBBS/Austin B Cycle Trip Data is accessed via the local government's Open Data Portal for the City of Austin (Docked Bike Data/Austin B Cycle Data, Retrieved from https://data.austintexas.gov/Transportation-and-Mobility/Austin-B-Cycle-Trips/tyfh-5r8s,), for a period of 8 months (July 2018 through February 2019). 133 MB of raw data is downloaded from the portal on Feb 2020, including trip data till Dec 2019 in.CSV format. The raw data contains individual trips, with attribute fields as Trip ID, Bicycle ID, Membership type, date, Checkout Date and Time, Kiosks (where the bicycles are checked out and returned), duration of each ride, month, and year as shown as a snapshot in Table 1. A total of 1.22 million bike trips are observed in the raw data, from where trips between July 2018 to February 2019 need to be extracted for this study purpose. Since the raw data is categorized in each bicycle trip based on membership type, the study also observes trips based on the different categories that are provided, which differentiates users with a regular membership, The University of Texas at Austin staff and student memberships, and casual riders who used this service. The Open Data Portal also provides a separate.CSV file of station locations, which includes Station ID, Station Name, and locations coordinates for easy geolocation of the stations, as shown in Table 2.

Dockless Mobility Data

Dockless mobility data is accessed via the same online portal used to download SBBS/Austin B Cycle data (Retrieved From https://data.austintexas.gov/Transportation-and-Mobility/Shared-Micromobility-Vehicle-Trips/7d8e-dm7r) on April 12, 2019. Dockless Shared Mobility Vehicle Trip dataset includes both raw data for free-floating bicycles and e-scooters and records a total of 4,137,069 trips. To analyze both dockless bikes and e-scooters, it is necessary to separate the vehicle type data into two separate files. 984 MB of raw data is downloaded from the portal.CSV format. The raw data contains attribute fields like Trip ID, Device ID, Vehicle type, Start and End Time of each trip, Month, Hour of the Day, Day of the Week, Year, Origin and Destination coordinates (up to 3 decimal places) as seen in the snapshot in Table 3.

Trip ID	Membership Type	Bicycle ID	Checkout Date	Checkout Time	Checkout Kiosk ID	Checkout Kiosk	Return Kiosk ID	Return Kiosk	Trip Duration Minutes	Month	Year
19099555	U.T. Members	095G	12/16/2018	0:00:08	3798	21st & Speedway @PCL	3838	Nueces & 26th	7	12	2018
19248817	U.T. Members	446	2/4/2019	0:00:09	2548	UT West Mall @ Guadalupe	3798	21st & Speedway @PCL	3	2	2019
19222130	U.T. Members	287	1/27/2019	0:00:22	3793	Rio Grande & 28th	2565	Trinity & 6th Street	14	1	2019
19248818	U.T. Members	2304	2/4/2019	0:00:29	3798	21st & Speedway @PCL	3798	21st & Speedway @PCL	592	2	2019
19099556	U.T. Members	2077	12/16/2018	0:00:35	2547	Guadalupe & 21st	3793	Rio Grande & 28th	11	12	2018
19208110	Non Members	429	1/22/2019	0:01:12	3390	Brazos & 6th	2563	Davis at Rainey Street	18	1	2019

Table 1: Snapshot of raw data for Docked Bike-sharing/ Austin B Cycle (Retrieved from https://data.austintexas.gov/Transportation-and-Mobility/Austin-B-Cycle-Trips/tyfh-5r8s,)

Kiosk ID	Kiosk Name	Kiosk Status	Latitude	Longitude	Location
3793	Rio Grande & 28th	active	30.29333	-97.74412	(30.29333, -97.74412)
3291	11th & San Jacinto	active	30.27193	-97.73854	(30.27193, -97.73854)
4058	Hollow Creek & Barton Hills	active	30.26139	-97.77234	(30.26139, -97.77234)
3797	21st & University	active	30.28354	-97.73953	(30.28354, -97.73953)
2546	ACC - West & 12th Street	closed	30.27624	-97.74831	(30.27624, -97.74831)
3838	Nueces & 26th	active	30.29068	-97.74292	(30.29068, -97.74292)
2544	East 6th & Pedernales St.	active	30.25895	-97.71475	(30.25895, -97.71475)

Table 2: Snapshot of Austin B Cycle Station Location (Retrieved from https://data.austintexas.gov/widgets/qd73-bsdg)

ID	Device ID	Vehicle Type	Trip Duration	Trip Distance	Start Time	End Time	Modified Date	Month	Hour	Day of Week	Council District	Council District	Origin Cell ID	Destination Cell ID	Year	Start Latitude	Start Longitud	End Latitude	End Longitud
000000cb-	ad14e63b-	scooter	358	915	6/29/2018 17:30	6/29/2018 17:30	12/12/2018 21:36	6	17	5	5	9	13445	13916	2018	30.263	-97.762	30.259	-97.754
00001b5f-	c5a230c9-	scooter	226	839	11/30/2018 11:00	11/30/2018 11:00	12/13/2018 15:43	11	11	5	9	9	14556	15186	2018	30.283	-97.745	30.284	-97.737
00002334-	5a9f7815-	scooter	324	1206	10/2/2018 15:15	10/2/2018 15:30	12/13/2018 15:49	10	15	2	9	9	15344	15032	2018	30.285	-97.734	30.291	-97.738
0000261e-	41fa0cf0-f	scooter	1096	0	9/2/2018 16:45	9/2/2018 17:00	12/13/2018 15:53	9	16	0	9	9	14707	14081	2018	30.268	-97.743	30.276	-97.752
00002c70-	ddd4bbc3-	scooter	408	1144	9/28/2018 11:45	9/28/2018 11:45	12/12/2018 22:24	9	11	5	3	3	16114	15642	2018	30.242	-97.721	30.244	-97.729

Table 3: Snapshot of raw data for Dockless Mobility Services (Retrieved from https://data.austintexas.gov/Transportation-and-Mobility/Shared-Micromobility-Vehicle-Trips/7d8e-dm7r)

DATA CLEANING

Before the analysis, it is necessary to check the data for consistency as well as identify potential issues in the raw data, such as missing data, missing coordinates, falsely labeled trips. Data cleaning is done in several stages as mentioned below:

Stage 1

Due to the large number of trips downloaded for both docked and dockless mobility mode, both the .CSV files will not open in MS Excel and even MS Access. It is necessary to filter out the unwanted trips and keep only the relevant data to the time of 8 months chosen for our analysis. Python is used in the following ways to parse and save the data in .CSV format before further filtering of data is done in MS Excel:

1. To parse out the unwanted trip data and keep the mobility trips that occur between July 2018 through February 2019.

2. In the case of dockless mobility data, it was necessary to distinguish and separate the bicycle trips from the e-scooter trips. Vehicle Type is used as the filter attribute.

3. Due to the high number of e-scooter trips, trip data cannot be saved into a single .CSV file as the trip counts exceeds the 1 million row capacity that MS Excel can hold. For dockless e-scooter data, further parsing is done based on the month attribute, and trip data is saved month wise as .CSV files.

Stage 2

After parsing the raw data using Python to obtain trips just for the 8 months, it is necessary to identify missing data issues along with a consistent unit of measurement for the attributes to be analyzed. This is done in the following steps:

1. Dockless data both bicycles and e-scooters have co-ordinate data listed either zero or blanks. Hence using MS Excel, it is necessary to filter out all the trips with this criterion.

2. Dockless data also included an O-D Cell to be listed as "OUT_OF_BOUNDS". These trips usually consist of either origin or destination locations not within the City of Austin as observed when mapping the trip points using ArcGIS. Out of bound trip-locations are filtered out to keep the consistency of the data.

3. Comparing all three types of trip data, it is noted that Time Duration/ Operation Time for each trip in the dockless category is in the "Seconds" unit whereas in SBBS/Austin B Cycle the time duration is calculated "Minutes". Hence, a new field is created and for converting the Time Duration field using the Excel formula "=CONVERT (cell number, "sec", "mn"), where "sec" is seconds and "mn" is minutes. Similarly, in Dockless data, trip distance is measured in "Meters". Using the same method, a similar formula of "=CONVERT (cell number, "m", "mi") where "m" in meters and converted to "mi" which is statute miles.

4. Data needed to be made consistent with each other, especially for analyzing the temporal patterns. Important attributes like hours of the day and day of the week

are important to analyze the temporal patterns of each type of mobility option. Both DSS and DBS are provided with this attribute. But in the case of SBBS data, both attributes are missing. Using the date attribute, a new field is created with the function "=WEEKDAY (cell number, return type). For this analysis, return type = 1, is chosen, which identified each day to a number. For example, 1= Sunday, 2=Monday, …. 7= Saturday. Since the dockless data already had an attribute "Day", which is numbered each day of the week on a different scale, it is necessary to convert and be consistent with the scale used for SBBS.

5. Using the formula Speed = Distance/ Time, the speeds for dockless mobility was calculated.

6. Using the formula Distance = Speed x Time, taking an average speed of 7.456 mph, the assumed distance traveled for station-based bike trips is obtained for later comparison (Langford, 2015).

Stage 3

After identifying the missing data, it is necessary to analyze the data and search for attributes that can serve as potential outliers in this analysis.

For SBBS trips:

a) Bike trips with a Time duration of zero minutes are taken out from the dataset.

b) Bike trips with time duration less than 1 minute are excluded from the dataset, because some of these trips may not be actual trips (Zamir et al, 2019).

c) Bike trips that lasted less than 2 minutes are not considered having the same origin and destination i.e. check-out and check-in locations (Zamir et al, 2019).

d) Trips lasting more than 24 hours are also taken out as a precaution, even though the dataset description mentions that bike trips in the dataset only contain trips lasting 24 hours (Austin Transportation Department, 2019; Zamir et al, 2019).

e) Trips more than 300 miles are excluded from the dataset.

For DSS trips:

a) E-Scooter trips with a time duration of zero minutes are not considered in the analysis dataset.

b) E-Scooter trips with a trip distance of zero miles are taken out of the dataset.

c) Since the dataset has both distance and time fields, the average speed for each trip is calculated. Any trip with an average speed slower than the average walking speed of 2.2 mph is excluded from the dataset, as they can imply a stop within a trip or error in the data (McKenzie, 2020).

d) All e-scooter trips identified more than 2 hours are taken out of the dataset because they unlikely seem to be authentic trips as e-scooters have a 2-hour battery life (roughly covering 30 miles of distance, using a maximum speed of 15 mph taken into consideration since the dataset doesn't give information regarding the operators) (Marshall,2018; Ellis, 2019; Toll, 2018).

e) E-scooter companies employ staff to charge e-scooters as well as redistribute scooters in places where either scooters have not been used or there are too many scooters lying around. Often staff goes to pick up a large number of e-scooters using cars, trucks, which have speeds much higher than that of 15mph termed as redistribution trips (McKenzie, 2019) Similarly, using the same concept, e-scooter trip more than 15mph are excluded from the dataset which may be termed as redistribution trips.

f) Further, only e-scooter trips more than 80 meters or 0.049 miles are considered as trips, almost considering it is a little more than half of the average block length in Downtown Austin (McKenzie, 2019)

For DBS trips:

a) Bike-sharing trips with a time duration of zero minutes are not considered in the analysis dataset.

b) Bike-sharing trips with a trip distance of zero miles are taken out of the dataset.

c) Bike-sharing trips, not more than 24 hours are taken into consideration for analysis in this dataset (Zamir et al, 2019).

d) Trips that were more than 300 miles are excluded in this dataset.

e) Since most of the dockless bicycles are electric, the exact maximum speed is much higher than a normal bicycle used mainly in the station-based sort. Hence any trip, with speed more than 50 mph are excluded to avoid outliers.

Stage 4

After taking into consideration the above criteria, the above data is put into STATA, to make a comparison between the three micromobility options. Using the longitude and latitude information provided for each of the micromobility options, the OD ground distance is calculated and tagged as "ODTripdist". The difference between the reported trip distance and "ODtripdist" suggests that the user deviates from the path and is engaged in other activities or deviating from the path while on the trip due to reasons like congestion or may take a longer route. Hence, another variable "Activity" is created which is the ratio of the reported distance to ODtripdist, which measures the extent to which the user deviates from the original path.

METHODOLOGY

Using the filtered data for 8 months, the study will try to answer the three research questions that are proposed in this report.

1. Whether the three specific micromobility modes display variations taking into consideration:
    a. Temporal variables like seasons, time of the day, days of the week, using trip volume, average operation time, average trip distance.

   b. Spatial distributions, thereby, visualizing trip data using ArcGIS across the City of Austin.

2. Whether three specific modes of micromobility: station-based bicycle-sharing, dockless bicycle-sharing, and dockless e-scooter sharing display substitutional or complementary characteristics.
3. Consider if the usage of the three micromobility modes is influenced by The University of Texas at Austin? (Since a typical bike user characteristic points to well educated (often with a college or higher degree) younger adult (typically between 21 to 45 years)).
4. In what ways can the City of Austin learn from the results to implement a successful transportation network and bridge the gaps?

The research will utilize the following:

1. Visualize trip volumes for the three modes for different days of the week as well as during seasons.
2. Summary statistics of the indicators like average trip times, average trip distance, "ODTripdist" to understand the differences between the three micromobility modes.
3. Using the above-mentioned indicators, summarize the variations (if at all) observed during the different seasons, day of the week, time of the day, as well as distinguishing between the different peak and off-peak hours, as well as weekdays and weekends.

4. The analysis will include hypothesis testing using ANOVA and T-Test Two Sample of Means, to understand whether the three modes are significantly similar or extremely dissimilar. The same indicators mentioned above are used for this portion of the research.
5. Using the software ArcGIS, the trips will be visualized to understand the spatial distribution of these trips across Austin, to determine whether these micromobility modes are dependent on The University of Texas at Austin.

To distinguish between the three modes, all three modes must be comparable. Since one of the most important factors which comes into play while making a comparison is the fact that the trip duration for DSS cannot exceed two hours since that is the battery life of a scooter. However, station-based bike-share and dockless bike-share include a trip time of more than two hours. Hence, to make all the three modes comparable, subsets of data have been taken from both SBBS and DBS, and then compared with the DSS, where Analysis of Variance (ANOVA) is used as a method to distinguish between the three modes. Similarly, the research also includes the comparison of station-based bike share and dockless bike-share, including all the trips occurring within 24 hours, which are not left out from the previous comparison. This comparison will utilize the T-Test Two Sample of Means.

To make the different comparisons, the data for the three micromobility options are coded as below for distinguishing the variations across seasons, days of the week, peak vs. nonpeak, and Weekday vs. Weekend. Since the data already included a consistent "hour of the day" category, the original category is used to summarize the data later. The initial indicators existing in the original data or after data cleaning via Excel are provided:

Category	**Code**
Day of the Week	
Sunday	0
Monday	1
Tuesday	2
Wednesday	3
Thursday	4
Friday	5
Saturday	6
Hour of the Day	
12 AM to 1 AM	0
1 AM to 2 AM	1
2 AM to 3 AM	2
3 AM to 4 AM	3
4 AM to 5 AM	4
5 AM to 6 AM	5
6 AM to 7 AM	6
7 AM to 8 AM	7
8 AM to 9 AM	8
9 AM to 10 AM	9
10 AM to 11 AM	10
11 AM to 12 PM	11
12 PM to 1 PM	12

Table 4: Original code used for differentiating data.

1 PM to 2 PM	13
2 PM to 3 PM	14
3 PM to 4 PM	15
4 PM to 5 PM	16
5 PM to 6 PM	17
6 PM to 7 PM	18
7 PM to 8 PM	19
8 PM to 9 PM	20
9 PM to 10 PM	21
10 PM to 11 PM	22
11 PM to 12 AM	23
Month	
July	7
August	8
September	9
October	10
November	11
December	12
January	1
February	2

Table 4 (Continued)

This analysis breaks the eight-month study period down into the following categories:

1. Weekday Vs. Weekends: In this case, the days of the week from Monday to Friday are considered as Weekdays. Saturday and Sunday are taken as weekends.
2. Peak V. Off-Peak: This research is considering 4 peak hours, compared to the two conventional peak hours of morning peak (7 AM to 9 AM) and Evening Peak (4 PM to 6 PM). The four different peaks considered are Morning Peak (7 AM to 9 AM), Midday Peak (11 AM to 1 PM), Afternoon Peak (4 PM to 6 PM), and Evening Peak (9 PM to 11 PM). Since a majority of the dockless scooters and dockless bicycles operate around Downtown and The University of Texas at Austin, we expect that Midday Peaks and Evening Peaks will show up as times when normal users/UT students and staff may use this service to either go for lunch or leave from the university/work to return home.
3. Seasons: Since this research is considering that young people are positively associated with micromobility, the operation of the University may influence the usage, depending on whether the school is in session. Hence the study divides the eight-months into four categories of seasons, Early Spring (Months January and February), Summer (July and August), Fall (September and October), and Winter (November and December).

The following table provides the new codes used for the analysis to understand the variation on the data based on the seasons, peak hours/off-peak hours, and weekdays/weekends:

Category	**Code**	**New Category**
Day of the Week		**Weekday/Weekend**
Sunday	0	**Week = 1**
Monday	1	**Week = 0 (WEEKDAYS)**
Tuesday	2	
Wednesday	3	
Thursday	4	
Friday	5	
Saturday	6	**Week = 1**
Hour of the Day		**Peak/Non-Peak**
12 AM to 1 AM	0	**Peak = 0 (OFF PEAK)**
1 AM to 2 AM	1	
2 AM to 3 AM	2	
3 AM to 4 AM	3	
4 AM to 5 AM	4	
5 AM to 6 AM	5	
6 AM to 7 AM	6	
7 AM to 8 AM	7	**Peak = 1 (MORNING PEAK)**
8 AM to 9 AM	8	
9 AM to 10 AM	9	**Peak = 0 (OFF PEAK)**
10 AM to 11 AM	10	
11 AM to 12 PM	11	**Peak = 2 (MIDDAY PEAK)**
12 PM to 1 PM	12	

Table 5: New code made to check variation.

1 PM to 2 PM	13	**Peak = 0 (OFF PEAK)**
2 PM to 3 PM	14	
3 PM to 4 PM	15	
4 PM to 5 PM	16	**Peak = 3 (AFTERNOON PEAK)**
5 PM to 6 PM	17	
6 PM to 7 PM	18	**Peak = 0 (OFF PEAK)**
7 PM to 8 PM	19	
8 PM to 9 PM	20	
9 PM to 10 PM	21	**Peak = 4 (EVENING PEAK)**
10 PM to 11 PM	22	
11 PM to 12 AM	23	**Peak = 0 (OFF PEAK)**
Month		**Season**
July	7	**Season = 2 (SUMMER)**
August	8	
September	9	**Season = 3 (FALL)**
October	10	
November	11	**Season = 4 (WINTER)**
December	12	
January	1	**Season = 1 (EARLY SPRING)**
February	2	

Table 5 (Continued)

The results of the analysis of the above data are included in the following chapter.

Chapter 5: Results and Analysis:

The study first analyzes the total trip count, total miles traveled by riders, total operational time, average distance, and average operation time, as well as the number of operational vehicles available during the period between July 2018 to February 2019 for all the three different micromobility options, the results of which are shown in Table 6, Table 7, and Table 8 respectively. Out of the three micromobility options, Dockless Bike-Share (DBS) has the lowest trip volumes. This is because it is the latest addition to the existing micromobility service introduced into the City of Austin's transportation fabric. Even though Station Based-Bike Share (SBBS) (Austin B Cycle) has existed for a much longer period compared to free-floating services, the highest trip volume was observed in the case of dockless e-scooters. In the following paragraphs, the logistics of the three types of micromobility modes are discussed based on the analysis conducted on the data gathered from the Open Data Portal. In the case of the two bike-share systems, all trips having an operational time of 24 hours are considered as genuine trips and taken into the dataset. For the free-floating e scooters, Operator Lime mentioned on their website, the battery life of scooters is two hours. Hence, trips with operational time within two hours are considered legitimate trips in our dataset.

DOCKLESS BIKE SHARE (DBS):

93,971 users prefer using free-floating bicycles during the study period, with the highest trip records for November, having the lowest average operational time and trip distance during the study period. Users traveled 171,434 miles over 1.827 million minutes (roughly 1269 days) during the eight-months, as seen in Table A. An increase in the number of vehicles available is visible from the start of the period till the end. On average, each free-floating bike share user spends about 19.45 minutes operating the vehicle to travel a distance of 1.82 miles. The month of December has the lowest trip count, consisting of 5% of the total number of trips occurring between July 2018 and February 2019, with an average operational time almost equal to the average operational time observed during this study period. Illustration 1 and 2 give the readers a visual depiction of the trip density locations by Origins and Destinations for DBS.

Dockless Bikes						
Total number of Trips = 93971						
	Trip Count	**# of Operational Vehicles**	**Total Trip Distance (Mi)**	**Total Operation Time (Min)**	**Average Trip Distance (Mi)**	**Average Operation Time (Min)**
July	6745	247	15044.60	164109.30	2.23	24.33
August	10109	478	21442.69	218506.87	2.12	21.62
September	11797	556	22427.98	255986.70	1.90	21.70
October	17478	521	32783.04	352029.83	1.88	20.14
November	21025	585	33290.19	359368.92	1.58	17.09
December	4711	698	7941.67	90085.92	1.69	19.12
January	9637	1005	17096.06	171840.73	1.77	17.83
February	12469	843	21408.36	215855.80	1.72	17.31
Total	93971		171434.60	1827784.07		
Average (8 months)	**11746.37**	**616.63**	**21429.32**	**228473.00**	**1.82**	**19.45**

Table 6: Summary statistics of Dockless Bikes Share (DBS)

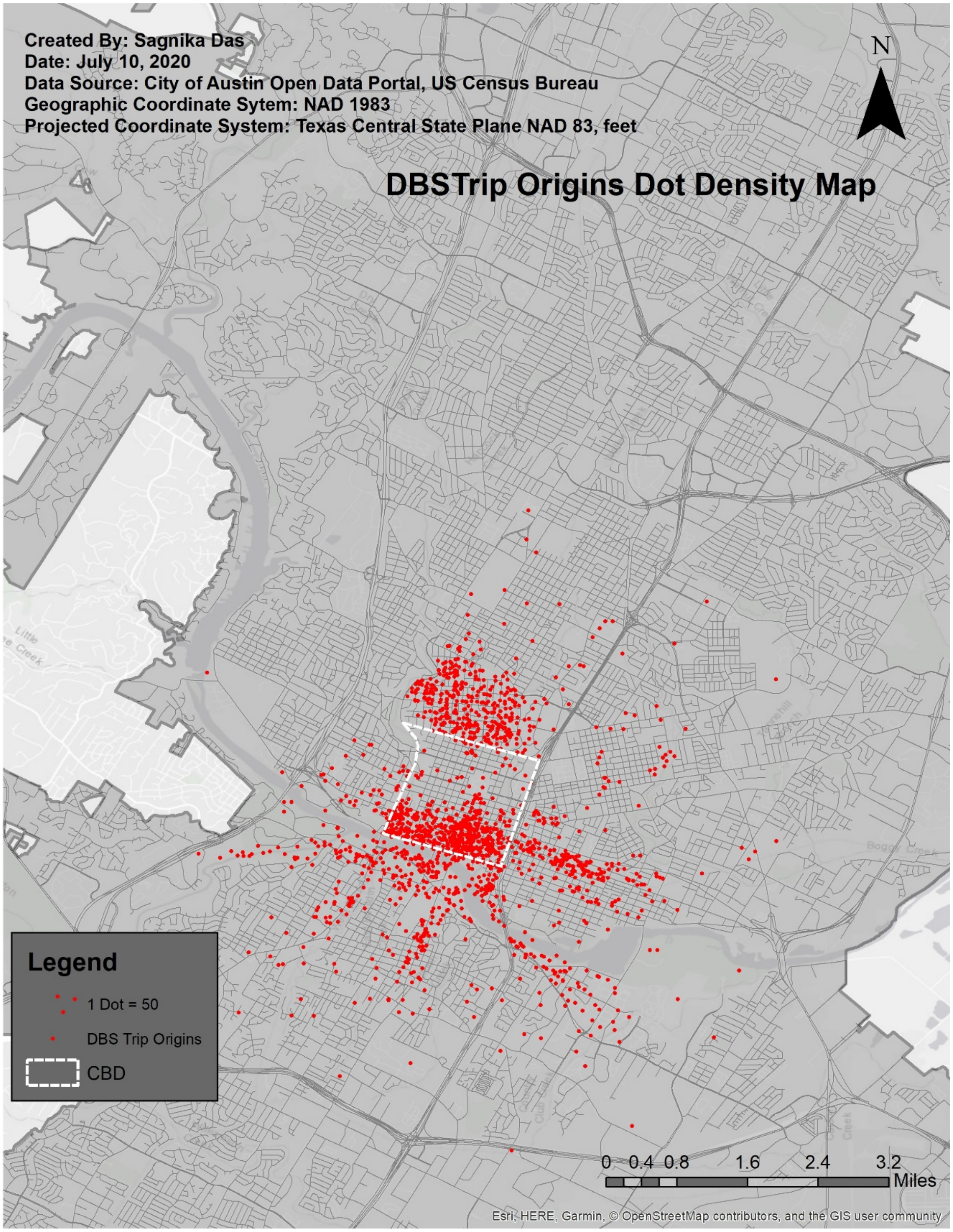

Illustration 1: DBS Trip Origin Dot Density Map

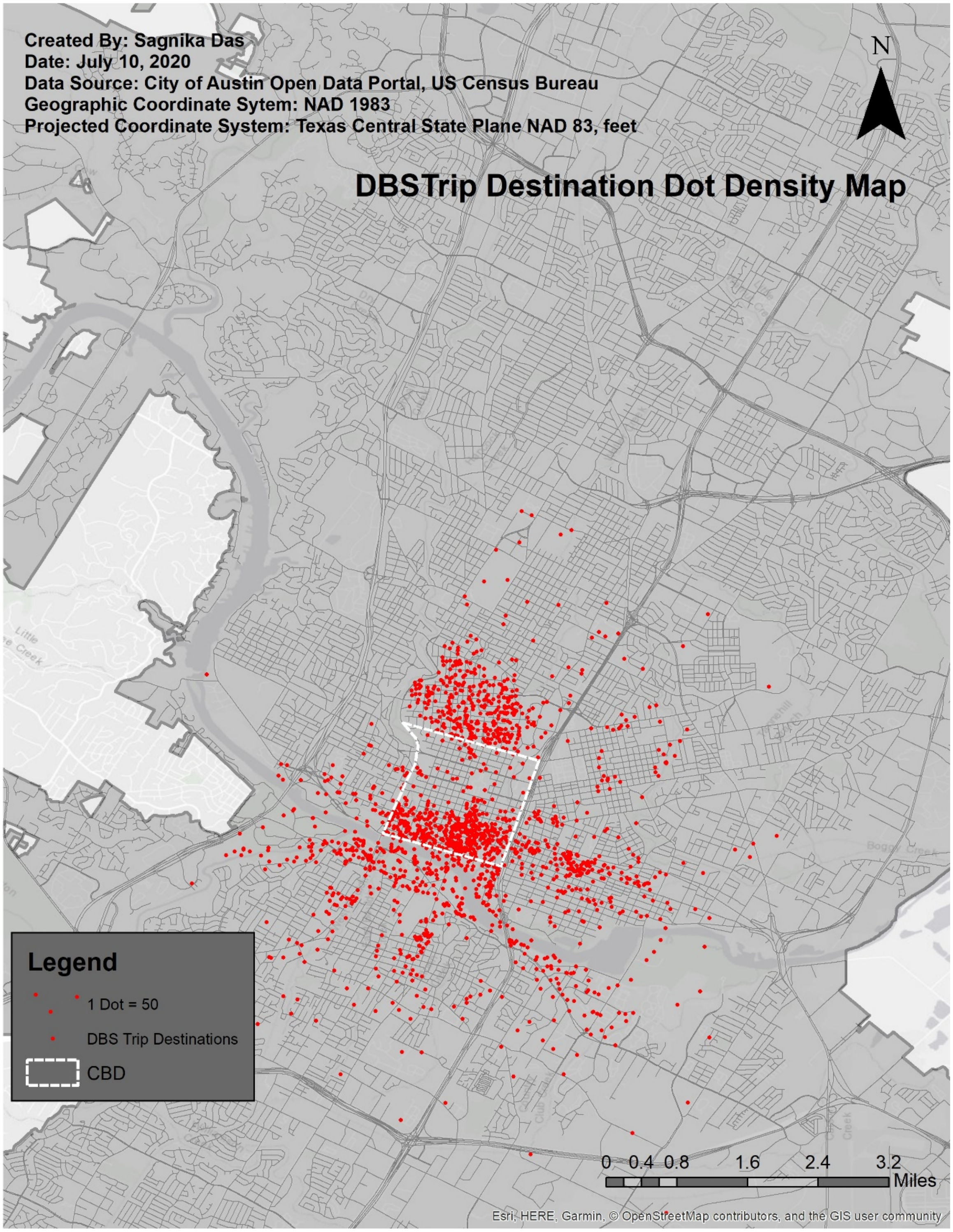

Illustration 2: DBS Trip Destination Dot Density Map

Both the Dot Density Maps, help in visualizing the areas where DBS Trip locations (both Origins and Destinations) seem to be concentrated. It is evident from both the maps that the Central Business District (CBD) area, particularly between 7th Street to Cesar Chavez, Rainey Street District, The University of Texas at Austin, West Campus are favorite locations where DBS trips are both generated and attracted, with maximum trip concentrations. Locations between East 7th Street and East 4th Street has a lot of trip concentration, especially near the Huston-Tillotson University, where a lot of recreational destinations are found. Both north and south of the Colorado River generate and attracts significant numbers of DBS trips, where Zilker Park, Anne and Roy Butler Hike and Bike Trail and multiple small parks are located. East Riverside Drive also receives and produces significant DBS traffic, near one of the prime locations where student housing exists in Austin. No distinguishable patterns can be observed between the Origins and Destinations; hence an assumption can be made that trips occur within proximity to the origins.

Figure 3 shows the distribution of trip counts for DBS across the days of the week. For both days over the weekend, along with Thursday and Friday, show higher numbers of free-floating bicycle trips for the week. (Count Table Appendix A) Saturdays record the highest trip count for the week (16768 trips) followed by Fridays (14739 trips) and Sundays (14675 trips). Weekends show trip peaks between 3 PM to 4 PM, where only Saturdays record a higher number of evening trips between the two days. Since the second-highest trips occur on Friday, both Saturdays and Friday evenings show a higher number of cumulative trips taking place between 7 PM to 12 AM, which is not observed in case of the other weekdays or Sundays. During the. weekdays, distinct peak trips are observed during two particular periods, between 8 AM to 9 AM and 5 PM to 6 PM, which falls between the conventional peak hour periods (between 7 AM to 9 AM and 4 PM to 6 PM).

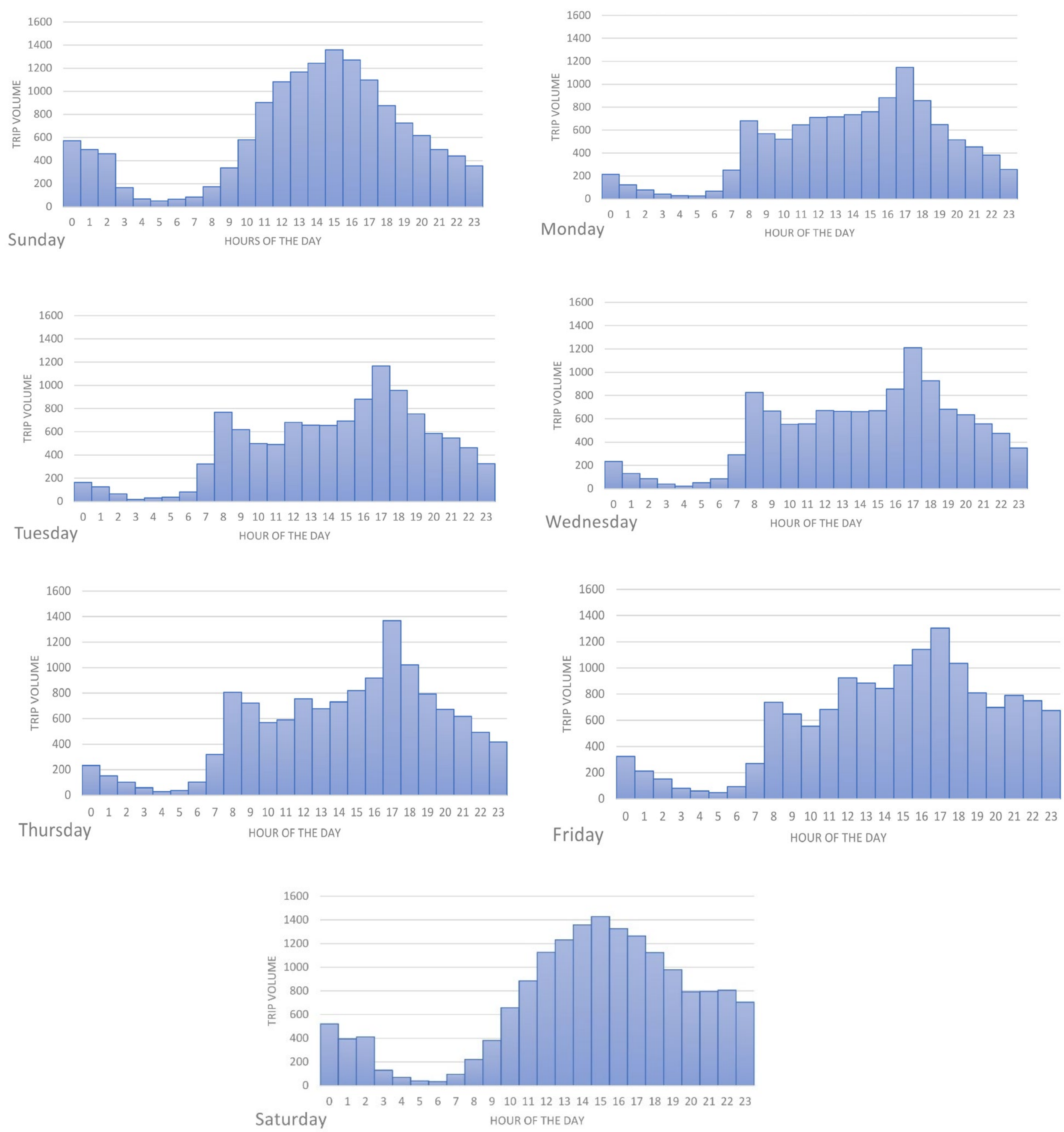

Figure 3: Trip Volume for DBS (Calculated using the table from Appendix A)

Multiple smaller peaks are observed throughout the week, but 12 PM and 1 PM gains prominence during Thursdays and Fridays, which may be considered as the midday peak. This evidence correlates with previous research finding that during weekdays, peak times occur between 8 AM to 9 AM during the morning, and at 5 PM during the afternoon (Zamir et al, 2019; McKenzie, 2018). Zamir et al (2019) also record weekends peak time at 3 PM, which is similar to the above findings. It is also seen that weekends account for a higher trip count than compared to the rest of the week as stated by Zeng et al (2020) previously.

STATION BASED BIKE SHARE (AUSTIN B CYCLE/SBBS):

Station Based Bike Share observes more than 1.5 times the number of DBS trips during these 8 months, a record of 153,797 trips. The highest number of trips is seen during September, which records the lowest trip distance of 2.32 miles and lowest average operational time of 18.71 minutes. Bicyclists traveled a total of 511,318 miles over 4.118 million minutes throughout the 8 months. The number of operational vehicles is almost consistent during this period because fleet size depends on the number of docking stations available, and the variation is dependent on the availability of bikes versus the demand for the micromobility mode. The average amount of time users operates the vehicles is 26.78 minutes to travel 3.32 miles as shown in Table B. Within the SBBS dataset only 19.7% of trips account for casual users and 13.5% of trips for normal membership. UT Student and Staff membership (66.7%) consists of the largest share. A Dot Density map is used in Illustration 3 and 4 to spatially show trip density locations for both the Origins and Destinations of the SBBS users.

Station Based Bike Share (Austin B Cycle Riders)						
Total number of Trips= 153797						
	Trip Count	**# of Operational Vehicles**	**Total Trip Distance (Mi)**	**Total Operation Time (Min)**	**Average Trip Distance (Mi)**	**Average Operation Time (Min)**
July	20608	468	65567.32	528130	3.18	25.63
August	21686	466	60274.68	485499	2.78	22.39
September	35524	461	82531.42	664772	2.32	18.71
October	25670	453	79305.76	638790	3.09	24.88
November	19287	448	66515.08	535764	3.45	27.78
December	11505	434	56702.76	456728	4.93	39.70
January	9051	427	38454.46	309742	4.25	34.22
February	10466	420	61967.34	499133	5.92	47.69
Total	153797		511318.83	4118558		
Average (8 months)	**19224.63**	**447.13**	**63914.85**	**514819.75**	**3.32**	**26.78**

Table 7: Summary Statistics of Station Based Bicycle Share (SBBS)

In the case of SBBS, it is difficult to understand the exact locations where the users start and end their trips, as they are bounded by the docking stations. If the origin or destination is near the stations, then the user's trip starts and ends at the docking stations, whereas if the stations are far off from the users' actual origin and destination, then the trip involves walking/commuting to the docking station, using the bicycle to reach a docking station near the destination and then walking/commuting to the destination. The Dot Density maps below simply helps readers to visualize popular docking locations, assuming that the origins and destinations of these trips are within proximity (Illustration 3 and Illustration 4).

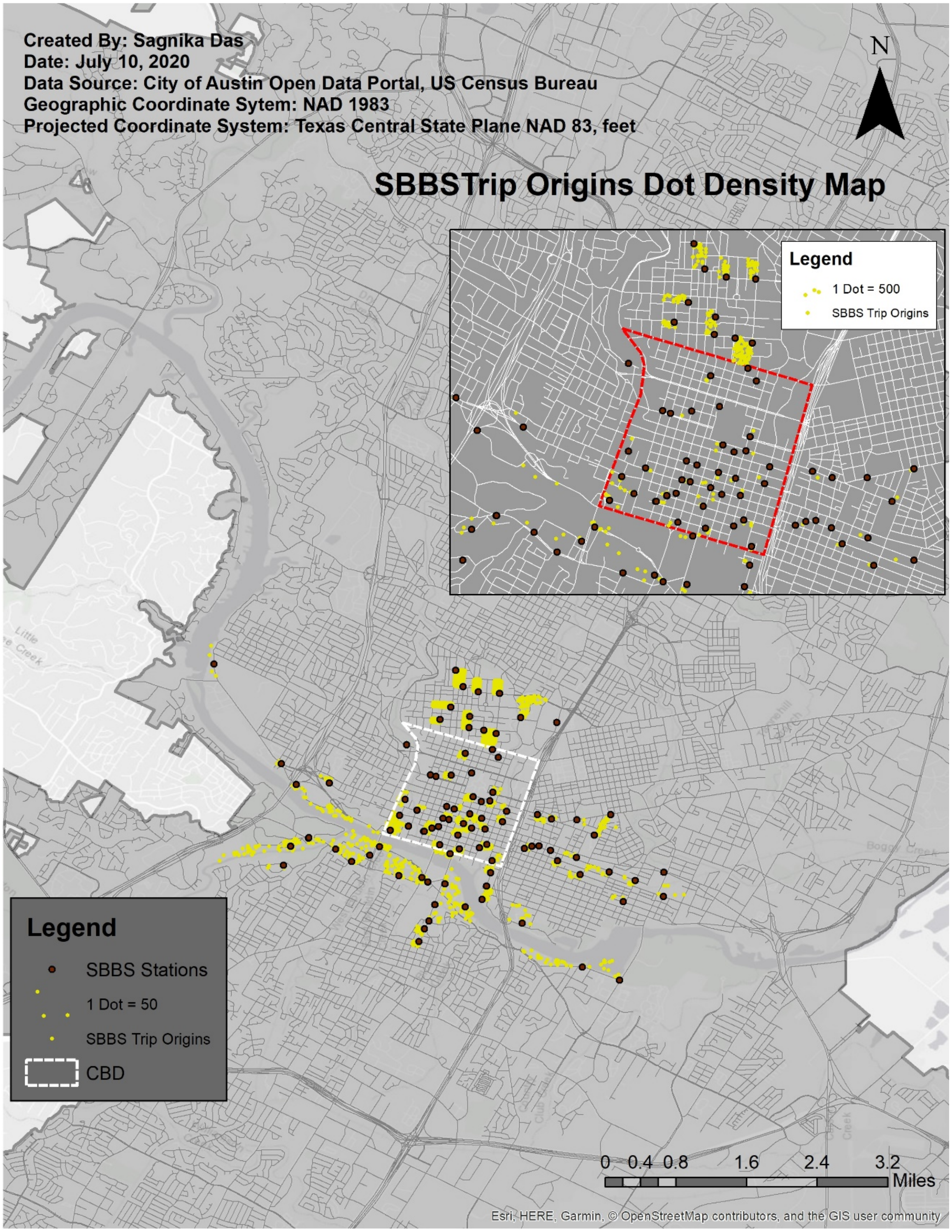

Illustration 3: SBBS Trip Origin Dot Density Map

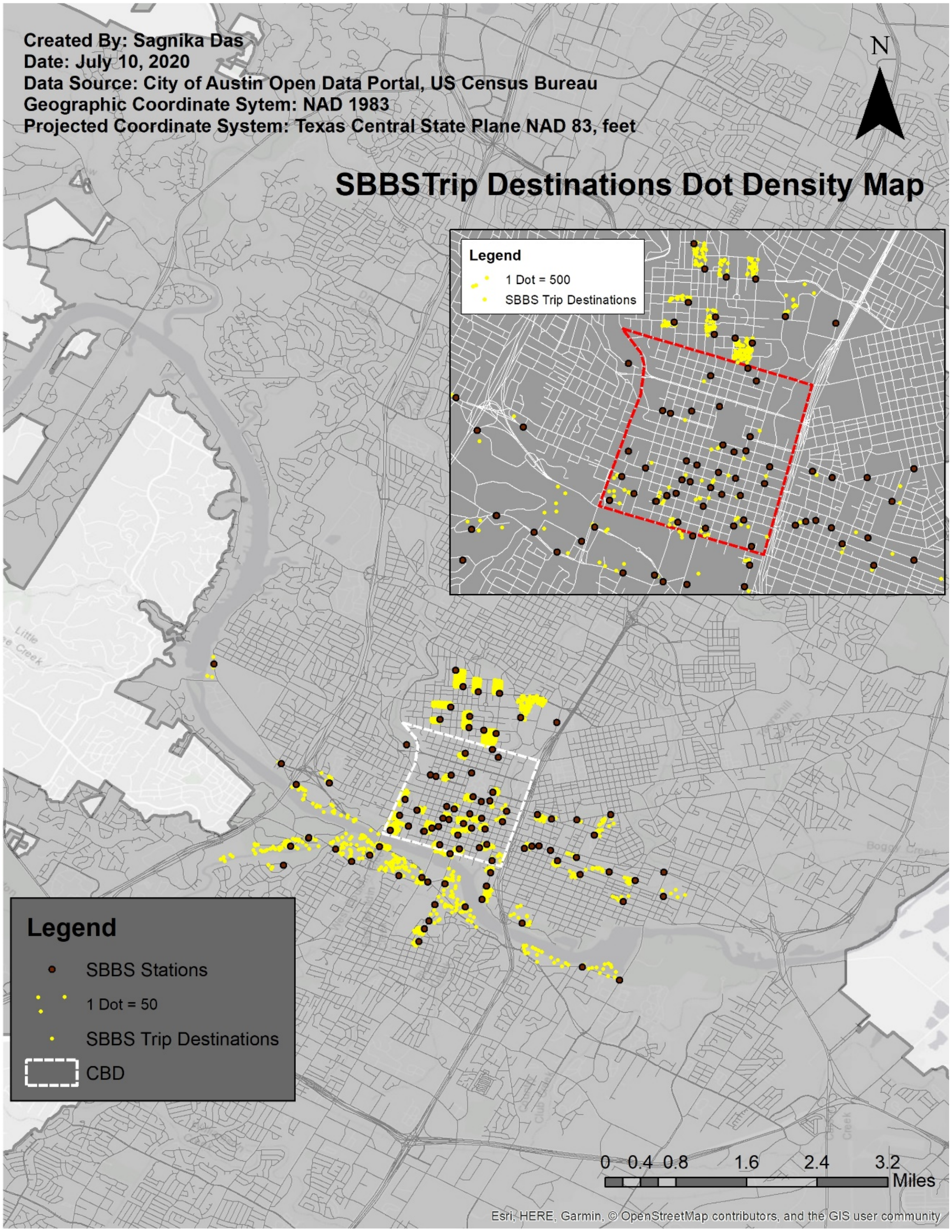

Illustration 4: SBBS Trip Destination Dot Density Map

From both the maps it is evident that docking stations located at The University of Texas at Austin, West Campus, 6th to 8th Street, on Cesar Chavez and along the riverfront, at Zilker Park and Auditorium Shores, East 12th Street near Huston Tilotson University seem to produce and attract significant trips when compared to DBS. But since the trip count for SBBS varies significantly in comparison to DBS, it is necessary to increase the scale to truly understand which locations are significantly increasing both trip counts as generators and attractors. Zooming into these maps, it can be understood that in the case of SBBS, docking stations located at The University of Texas and West Campus provide maximum trips. The docking locations around these two-particular areas, provide trip concentration as origins and destinations. Since 66.7% of the total trips used the UT Student and Staff membership privileges, it is logical that trips will be concentrated around these two areas since both locations are significant to the UT population, where the University provides education and employment to thousands of people, West Campus is a key residential location for UT Students in Austin.

Figure 4 shows the trip count number of SBBS across the week, for 24 hours. Highest trips per day are seen on Thursdays, Fridays, and Saturdays, with Friday leading with 23,398 trips, then Thursday (22,970 trips), and Saturdays (22,815 trips) respectively (Count Table Appendix A). Weekend peak times occur between 12 PM to 1 PM on Sundays, and 1 PM to 2 PM on Saturdays. In the case of Weekdays, no distinct peak times are observed. Multiple periods with high numbers of trip counts are seen throughout the weekdays. Morning peak times occur between 9 AM to 10 AM (Mondays, Tuesdays, Wednesdays) and 10 AM to 11 AM (Tuesdays, Thursdays, Fridays). Midday peaks take place between 12 PM to 1 PM and 1 PM to 2 PM for weekdays, a pattern not seen in the DBS system. Evenings between 5 PM and 6 PM account for the evening peaks during the weekdays, with the highest trip-counts, observed for the day.

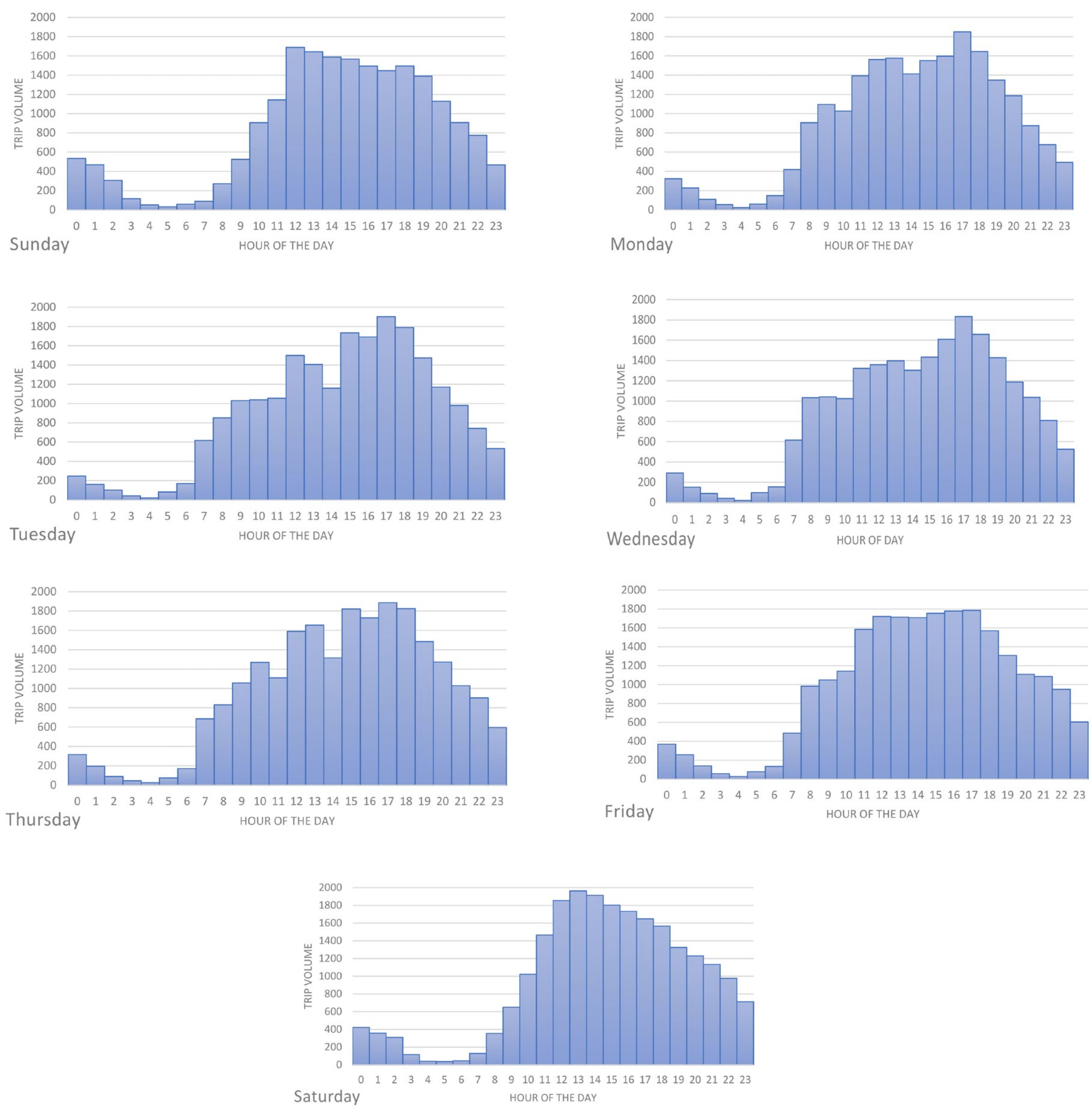

Figure 4: Trip Volume for SBBS (Calculated using the table from Appendix A)

Now in comparison to evidence found by Zamir et al (2019), stating that Thursday accounts for highest SBBS member trips, and Weekends for casual riding, this research observes Thursday accounting for the highest overall trip count for the week, with Fridays, Saturdays, and Sundays with correspondingly higher counts compared the rest of the week. In this case, Friday holds the maximum trip counts for the week followed by Thursday. This points out to the fact that since SBBS contains both members and casual riders, it is hard to distinguish which group accounts for the higher number of trips during these days. Within the SBBS dataset, only 19.7% of trips account for casual users, normal membership (13.5%), and UT Student and Staff membership (66.7%) consists of the larger share. With a higher number of overall trips for Thursday, Friday and Saturday, it is inferred that many members (21% of normal member trips, and 23% of UT Membership trips) utilize their membership privileges during the weekends as well, for non-commute trips. The higher counts for Friday is due to the higher number of trips made by members (13.5% by normal members and 64.2 % by UT members).

Even though Zamir et al's observation doesn't hold in this research, the fact that higher SBBS trips occur during a weekday is also a big eye-opener, because normally researchers expect weekends to account for higher trips, as people have more free time to make trips. According to McKenzie (2019), SBBS trips show peak times from 8 AM to 9 AM and 5 PM to 6 PM during weekdays. Similar morning peak observations have been made by other researchers as well (Zeng et al, 2020; Zamir et al, 2019). But this does not hold in this case. Higher trips are observed between 9 AM to 11 AM during the weekdays. One inference that can be made in this case is that since the majority of the trips made are by UT members, commute times may depend on work timing or class timing, and hence varies between that window. In case of the afternoon peak (5 PM to 6 PM), it corresponds to the observations made by McKenzie (2019) and falls within the conventional afternoon peak times, signifying that most classes or work ends around that time in Austin. Zamir et al (2019) claim that weekend peaks for SBBS members are within the window of 12 PM to 1 PM and for casual riders, it is 3 PM to 4 PM. In this research, it is seen that weekend peaks occur between 12 PM to 2 PM, much earlier than the time frames mentioned. This deviation may be due to a higher percentage of SBBS members participating in the weekend trip share (55% UT members and 18% normal members).

DOCKLESS SCOOTERS (DSS):

Out of the three types of mobility, dockless e-scooters count for the highest number of trips taking place during this period, where 2.13 million trips (as mentioned in Table (number)) took place over the 8-months. The month of February has the highest trips (339,976), during which the average operational time (9.75 mins) and reported trip distance (0.93 miles) (one of the least observed during the eight months). Riders traveled 22.9 million minutes (almost 15,918 days) and covered 2.1 million miles across the City of Austin. The number of trips increasing is consistent with the increase in fleet size, signifying that the availability of more vehicles makes more users utilize the free-floating mobility service. An average e-scooter user spends 10.76 minutes to travel 0.99 miles in Austin, from July 2018 to February 2019, as observed in Table C. Illustration 5 and 6 provides a Dot Density map which helps to visualize locations, both origins, and destinations for DSS users, where trips may be concentrated.

Dockless Scooters						
Total number of Trips = 2130296						
	Trip Count	**# of Operational Vehicles**	**Total Trip Distance (Mi)**	**Total Operation Time (Min)**	**Average Trip Distance (Mi)**	**Average Operation Time (Min)**
July	106778	1695	121304.93	1298393.53	1.14	1298393.53
August	263007	3466	281276.01	3044047.00	1.07	11.57
September	282972	6386	266276.12	2907219.40	0.94	10.27
October	294424	7362	275615.78	3040180.07	0.94	10.33
November	294679	12134	290564.81	3142921.02	0.99	10.67
December	274223	12641	277001.72	3074696.62	1.01	11.21
January	274237	11603	285016.77	3098968.77	1.04	11.30
February	339976	12939	319263.05	3315742.73	0.94	9.75
Total	2130296		2116319.20	22922169.13		
Average (8 months)	**266287**	**8528.25**	**264539.90**	**2865271.14**	**0.99**	**10.76**

Table 8: Summary Statistics of Dockless e-Scooter Share (DSS)

Unlike DBS and SBBS, DSS is more scattered across Austin, and not limited to the urban core. Both Illustrations 5 and 6 gives this proof while comparing with the trip counts of DBS and SBBS, where trip concentrations for both origins and destinations are located near the University and the southern part of the CBD, mostly from 7th Street to Cesar Chavez, DSS trips occur at the same rate throughout the CBD and the University of Texas at Austin, Downtown, on both sides of the riverfront, which includes Zilker Park, Lady Bird Lake, Riverside, and as far as the Barton Creek Green Belt. Mueller Market, Bartholomew Park, locations beside Guadalupe, Burnett, North Lamar, Airport Blvd, Pickle Research Center, and The Domain also constitutes significant trips even though location-wise, they are away from the city center. The destinations of DSS trips are slightly more spread out than their origins.

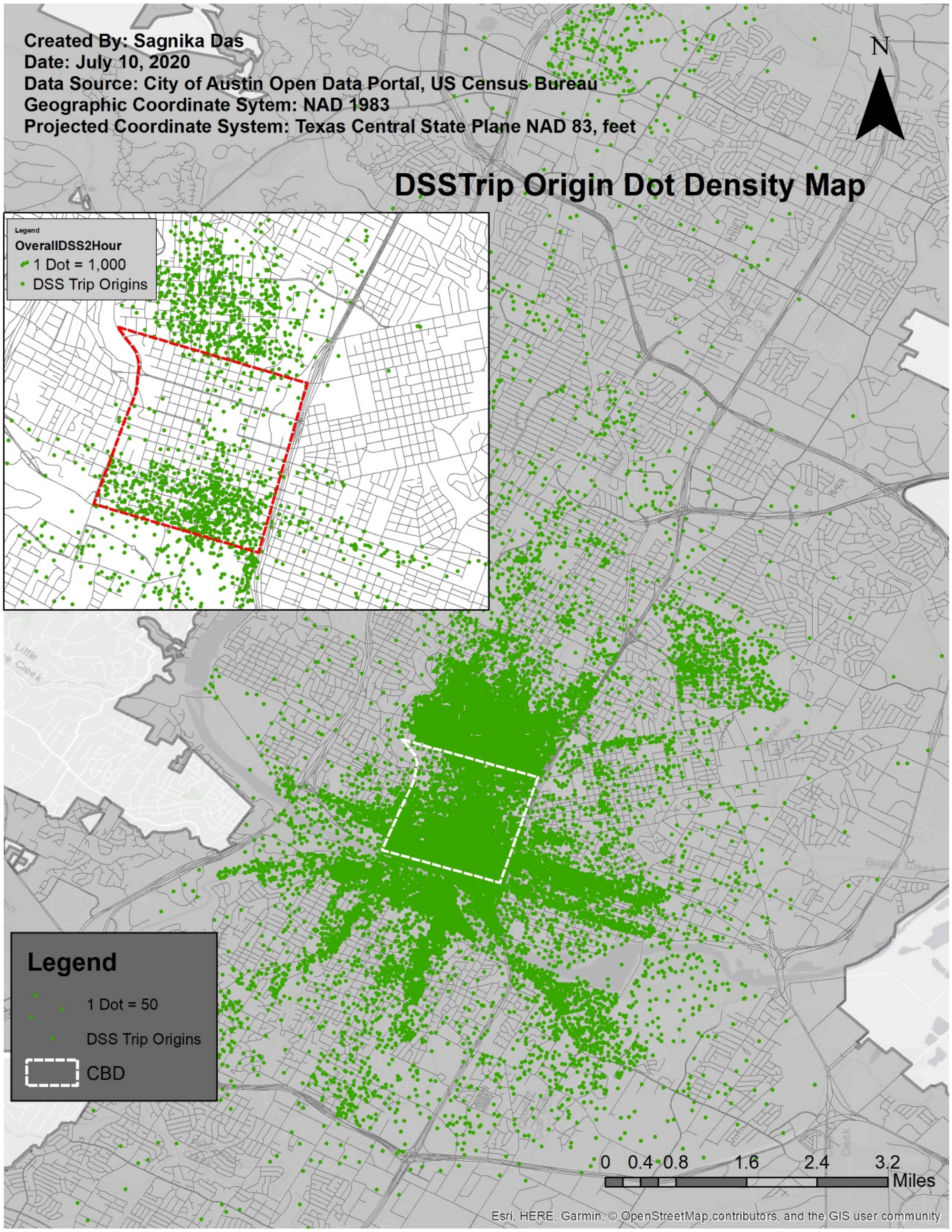

Illustration 5: DSS Trip Origin Dot Density Map

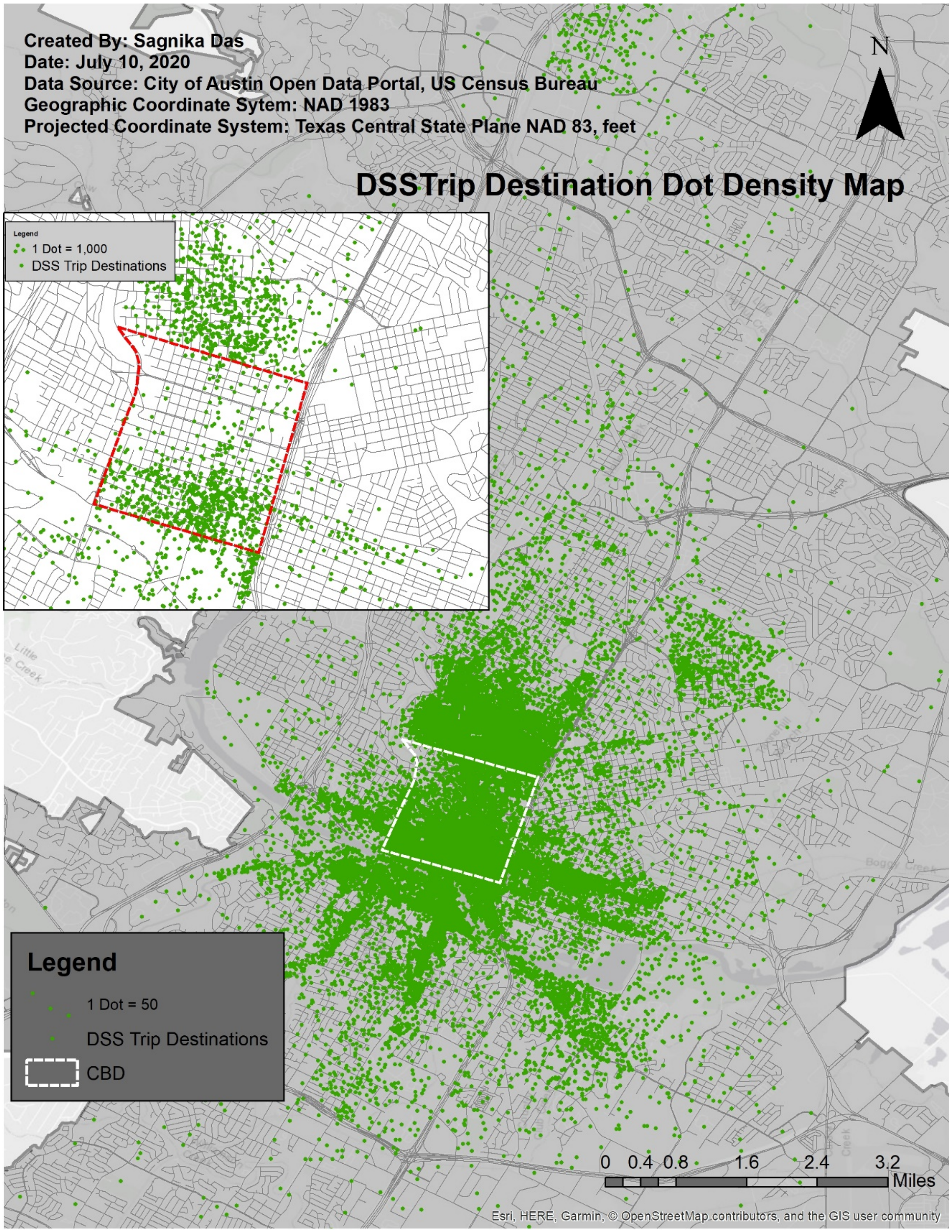

Illustration 6: DSS Trip Destination Dot Density Map

Since both Illustrations 5 and 6 give a comparison based on the trip counts for DBS and SBBS, where trips are comparatively less than DSS, it is necessary to distinguish trip concentrations individually to understand true locations where density maybe be higher. Hence, zooming into the CBD, and increasing the dot density count, it is observed that both the University of Texas at Austin along with the West Campus and southern part of Downtown are more concentrated than the rest of the locations. This is because initially the dot density count for all the three modes was set to be equal for comparison, but since each type of mobility had different trip counts, it was difficult to locate specific areas to show readers visually where true trip concentrations were located. Hence with the increase in dot count, it is evident now that just like DBS and SBBS, the prime locations for DSS users are the University of Texas at Austin, West Campus, and southern Downtown (specifically from 7th Street to Cesar Chavez), more along Congress Avenue.

In Figure 5 the total trip count is visually shown across the days of the week, distributed on the number of hours each day. Trip counts for free-floating e-scooters increases as the weekends, with higher trip counts during on Thursday, Fridays, and Saturdays in comparison to the rest of the week. Saturday, being a weekend, counts for the highest number of trips (358,167) for the week with Fridays (331613) and Thursday (312693) following it (Count Table Appendix A). Weekends show one single peak, but for both days, the window period varies. Sundays observe an evening peak between 3 PM to 4 PM; the peak shifts an hour back from 4 PM to 5 PM on Saturdays. On weekdays, no distinct peak times occur but multiple periods with an increase in trip counts are seen. On weekdays, the morning peak starts at a later time than the conventional model, which is between 10 AM to 11 PM. Distinct midday peak is also observed between 1 PM to 2 PM along with an afternoon peak between 6 PM and 7 PM (which is also an hour later than the conventional evening peak time).

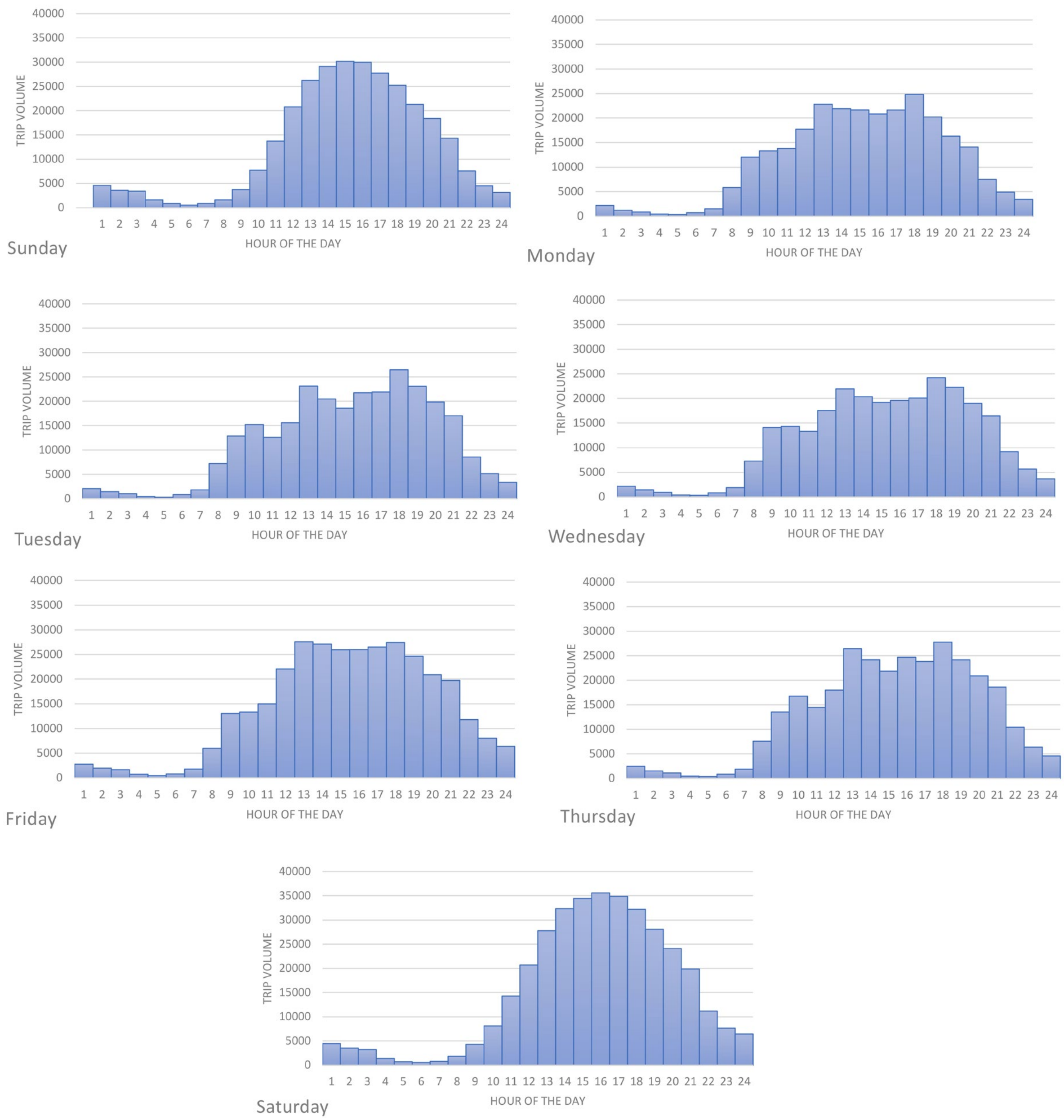

Figure 5: Trip Volume of Dockless e-Scooter Share (DSS) (Calculated using the table from Appendix A)

Younes et al (2020) state that DSS peak activity occurs during the weekend, with maximum trips observed on Saturday than Sunday. He also mentions that Friday trips are not statistically any different than Sunday trips, implying that the mean trip volumes may be almost similar for both Fridays and Sundays. This research only half agrees with Younes et al's claim, i.e., the highest trip count occurring on Saturday, followed by Fridays and Thursdays. Sunday trip counts account for only the fourth-highest value. But Younes et al, also mentions that Friday trips are similar to Sundays, implying that Fridays also have a higher number of trips after Saturdays, in comparison to the rest of the week, which matches the above-mentioned results. With the limited research related to e-scooters, Jiao and Bai's (2020) research directly affects the results obtained above, as both deals with the same type of data and study period for the City of Austin, where researchers conclude DSS weekday peaks occur at noon around midday and at 5 PM (same as the afternoon peak time). This echoes with the above research's findings, along with the fact that most trips start during the latter part of the morning, i.e., after 10 AM, with the majority of the trips occurring between 10 AM and 5 PM. Mathew et al (2019) conclude that most e-scooter trips start after 11 AM, and hence indicate that scooter share is not a significant choice for the morning commute.

From the above results, it is evident that people tend to use the micromobility modes more as the week approaches the weekend. For both the free-floating types, Saturdays account for the highest number of trips over the week, with an increase in the number of trips over Thursday and Friday. Sunday surprisingly does not account for even the second-highest trips for any of the three mobility modes, even though it can be assumed that weekends attract more users for recreational purposes. The trend observed for trip counts, for weekdays vs. weekends, is similar throughout the three micromobility modes, but with varying peak times, an hour before and after. Cumulatively, the peak hours for all the three types may range from 9 AM to 2 PM, for the morning and midday peak, and from 5 PM to 7 PM for the afternoon peak.

COMPARING THE THREE MICROMOBILITY MODES:

The second part of data analysis includes comparing the three types of micromobility options to look for variation within operation time, the time duration of trips, origin-destination distance, and activity ratio, using attributes like hours of the day, weekdays vs. weekends, peak vs off-peak times and seasons. To compare the three different types, a subset of DBS and SBBS is used for this portion of the analysis, since the DSS dataset only includes trips with a maximum operation time of 2 hours. Hence, for comparison, DBS and SBBS only include trips within 2 hours or 120 minutes. Now, with this new dataset, it is observed that the average operation time and average trip distance decreases comparatively both bike-share modes. For DBS, an average operation time of 14.73 mins (from 19.45 mins) is deduced for overcoming an average trip distance of 1.75 miles (from 1.82 miles). Similarly, for SBBS, on average a user rides a bike for 14.73 mins (from 26.77 mins) for a trip distance of 1.82 miles (from 3.324 miles). Figure 6, Figure 7, Figure 8, and Figure 9 visually depicts average operation time, average trip distance, average origin-destination distance, and average activity ratio for the different attributes considered earlier, from the results obtained from data in Appendix B.

Across the week, shown in Figure 6(A), average users report longer operational time during Saturdays and Sundays compared to the other days of the week, for all the three modes. The trend observed on both the free-floating mobility modes are similar i.e., both show the same rate of increase/ decrease between Fridays and Saturdays, and Sundays and Mondays, respectively. Only in the case of both bicycles, it is seen that average operation time users need on Saturdays tends to be almost equal (19.875 mins for DBS and 20.496 mins for SBBS). Figure 6 (B) echoes with the previous claim, from where it is seen that users travel increased average trip distances over Saturday and Sunday, using all the three types of micromobility. The rate of change observed for DBS and DSS is almost similar, whereas, in the case of SBBS, the average distance traveled by the riders is much higher over Saturdays and Sundays. This can be because members or users buying monthly, weekly, daily passes take the opportunity of utilizing the free one-hour rides that are available with the passes. The extra time is taken to find empty docking stations can occur during both weekdays and weekends and may not come into consideration as reasoning for the increased operation time. This can be verified in the future with research dedicated towards the breakdown of user groups for SBBS. Now DBS shows a concave curve in Figure 6(C) for average O-D Distance, opposite to that of SBBS and DSS. For DBS, Saturday and Sunday having lower average O-D distance signify that the destinations which people opt for generally are shorter for both days of the weekend compared to the rest of the week. On the other hand, in the case of SBBS and DSS, following a similar convex curve as observed in case of average trip distance (in Figure 6(B)) the destinations chosen for weekends are farther away as compared to weekdays.

A

B

C

D

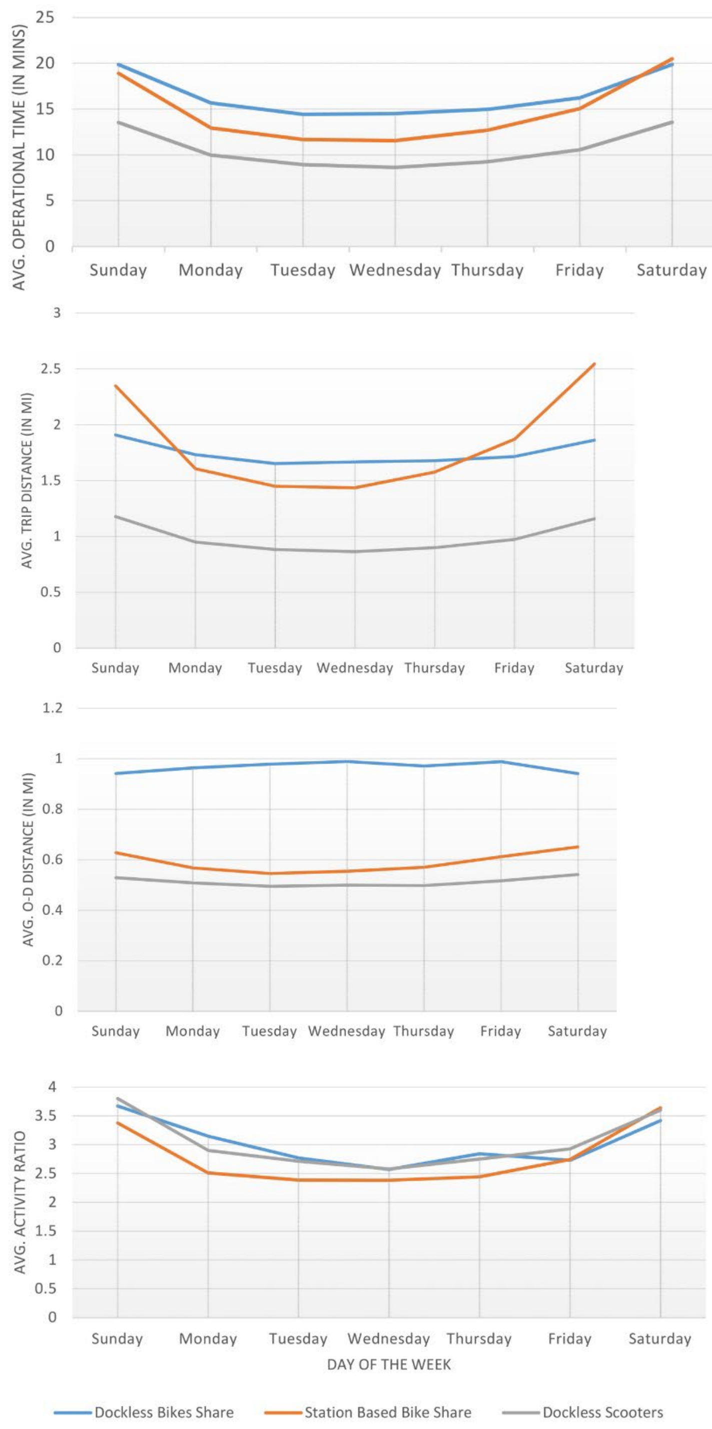

Figure 6: Comparison for Day of the Week: (A) Average Operational Time, (B) Average Trip Distance, (C) Average O-D Distance, (D) Average Activity Ratio

The Activity Ratio observed in Figure 6 (D) paints a different picture, where only trips with displacement are positive are taken into consideration. For free-floating mobility, this is any trip more than a block, and for SBBS, trips with different origin and destination stations are considered. Now over Saturday and Sunday, the rate of deviation from the original path (which is calculated by the O-D Distance) is higher (as observed from Trip Distance reported) for all the three types, compared to the rest of the days of the week, even though ups and downs exist within the weekdays. DBS only shows a slight increase in the activity ratio on Thursdays, meaning users deviate from their destinations much more compared to the rest of the weekdays

Comparing weekdays vs weekends, in Figure 7 (A) shows a similar rate of change in operation time for both the free-floating mobility options when comparing weekdays over weekends as well as increased reported average trip distance (Figure 7 (B)). SBBS observes a sharp increase in operation time as well as the reported trip distance from weekdays to weekends. This echoes with the previous deduction that SBBS users may take the opportunity of the passes that provide free rides up to an hour of use. The extra time is taken to find empty docking stations can occur during both weekdays and weekends and may not come into consideration as reasoning for the increased operation time. Figure 7 (C), also gives a similar result as observed earlier (Figure 6 (C)) when comparing the days of the week, where O D Distance for DBS over weekdays is higher than weekends, whereas both SBBS and DSS show an increase in distance of final destinations is chosen for the trip. In the case of the Activity ration observed for weekdays and weekends, cumulatively the rate of deviating from the original trip path is higher in all the three types of micromobility (Figure 7 (D)).

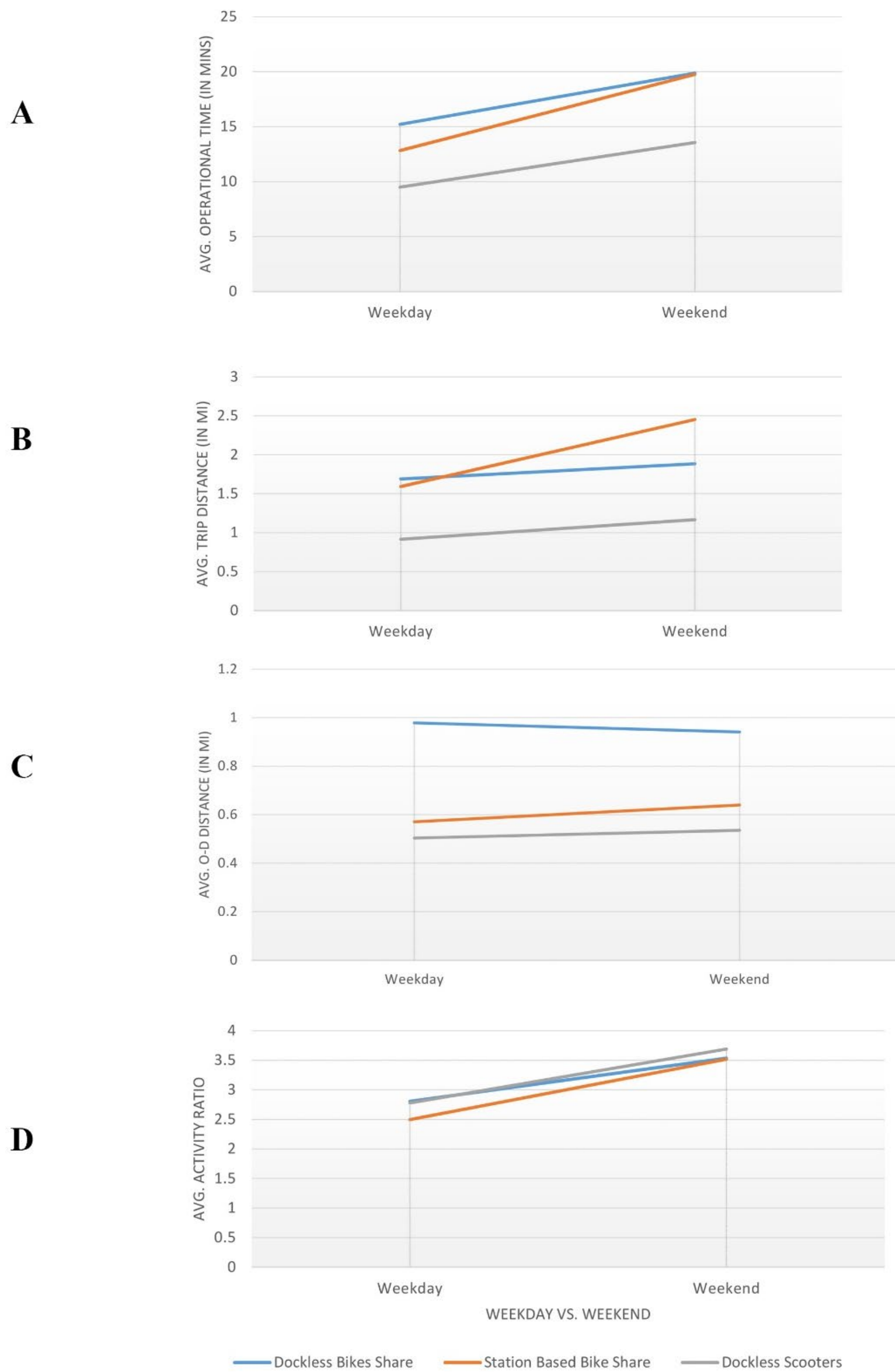

Figure 7: Comparison for Weekend vs. Weekday: (A) Average Operational Time, (B) Average Trip Distance, (C) Average O-D Distance, (D) Average Activity Ratio

Figure 8 (A) compares the average operation time across assumed peak times vs. off-peak hours of a day. Morning Peak (between 7 AM to 9 AM) shows the least operation time during incase of all three mobility options, with the highest average operation time for DBS and SBBS during lunchtime (between 11 AM and 1 PM). For DSS users, maximum average operation time is observed during the afternoon peak hours (between 4 PM and 6 PM). The second-lowest operation is observed during the evening peak (9 PM - 11 PM) for all modes of transport, whereas Off-Peak operations are consistent and high, compared to Afternoon and Evening Peaks. However, a similar trend is not observed in the case of average trip distance as shown in Figure 8 (B). Morning Peak for SBBS and DSS show the least trip distance, whereas, for DBS, this scenario occurs during the Evening Peaks. SBBS users have been shown to travel the highest average distance during the Midday Peak (11 AM - 1 PM). In the case of DBS, it is observed that users travel the highest average trip distance taking lower operation time. This can suggest that DBS users are not traveling in areas where most of the congestion occurs. According to Figure 8 (C), it is observed in all three mobility types that O-D Distance is the highest during the Morning Peak, with the least difference being shown with reported average trip distance. This suggests that users in the mornings complete their trips with the least deviation compared to the other times. On the other hand, DBS and SBBS users deviate the most, when on trips, suggesting they conduct intermediate activities traveling from origin to destination. In the case of DSS, the maximum path deviation is shown during the Afternoon Peak (between 4 PM to 6 PM). Since this is a congestion period, it can be concluded that the scooter users fall under the prey of traffic and travel using alternate longer routes to reach their destination. The Activity Ratio graph in Figure 8 (D) shows DBS users deviating more than 3.5 times from O-D distance during Midday Peaks for longer distance trips, which echoes with the previous assumption that DBS trips deviate maxim during midday peaks. For SBBS, this maximum deviation also takes place during the same time frame, but for DSS it occurs during the afternoon Peak. At the same time, it is observed that Morning Peaks show the least amount of deviation for all three types of mobility, suggesting that users promptly reach their destinations without stopping in between for other activities.

When considering the seasonal variation, it is observed in Figure 9(A), that the average operation time is highest during Season 2 (for months July and August) for free-floating micromobility, but for SBBS it is during Late Spring(during months January and February), Different mobility options have different seasons when users take the least amount of time to travel, which is consistent with the least reported average trip distance for each of the cases (Figure 9(B)). Higher average trip distance is observed for SBBS during late spring, whereas in the case of DBS and DSS, it is during the initial periods when free-floating micromobility was introduced in Austin. It is generally not expected that users spend more time and travel increased distances during summer, especially when temperatures are high. But an assumption can be made that since both mobility options were just introduced, it may have invoked curiosity amongst its new users, regarding its usage. The average origin-destination distance as seen in Figure 9(C) gives is highest in Summer for DBS and Late Spring for SBSS and DSS. It is the lowest during Winter for DBS and during Fall for both SBBS and DSS, from where it can be assumed that shorter period trips were taken by the SBBS and DSS riders during Fall and DBS in Winter, showing the least deviation during this period. For longer trips, maximum deviation is observed during Summer for all the three micromobility options. The least deviation is shown during different seasons for the three micromobility option, Fall for SBBS, Winter for DBS, and Late Spring for DSS.

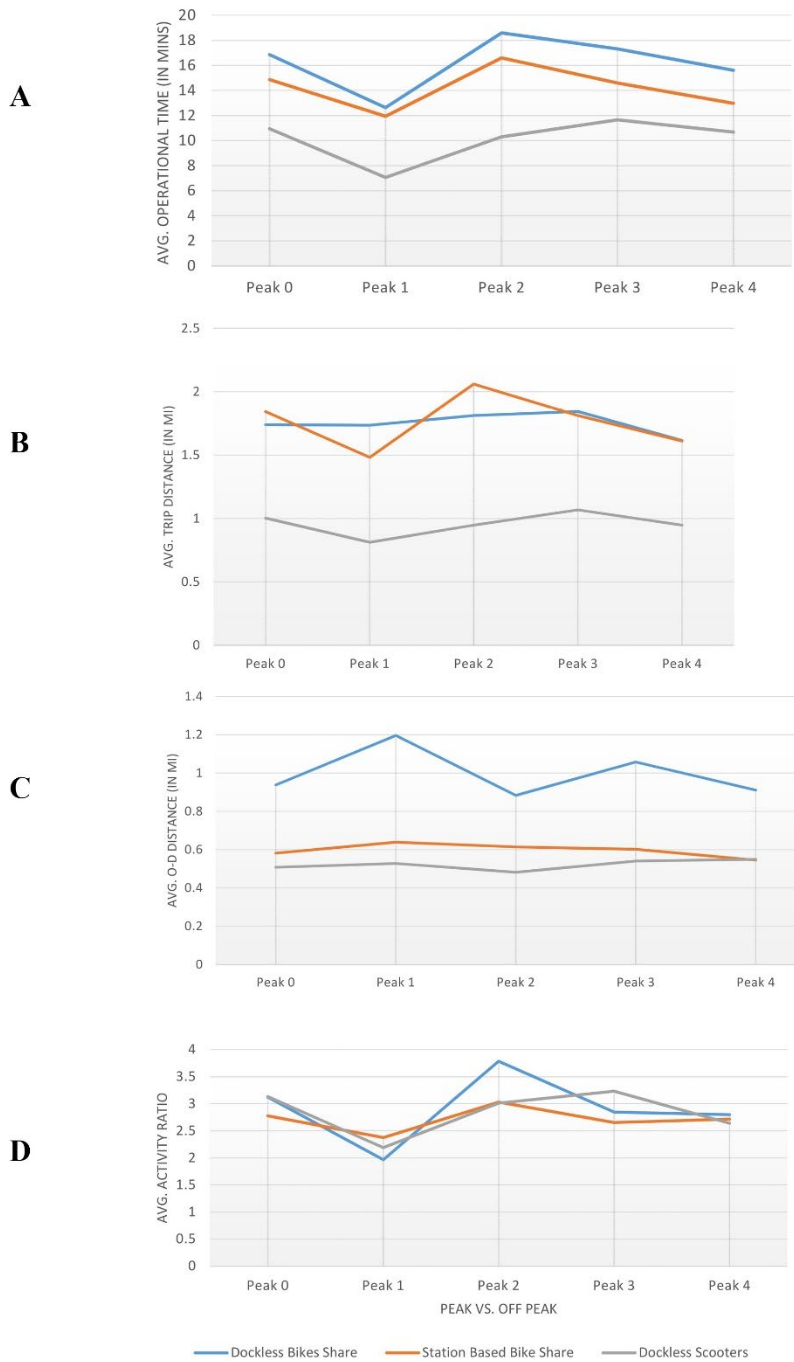

Figure 8: Comparison for Daily Peaks: (A) Average Operational Time, (B) Average Trip Distance, (C) Average O-D Distance, (D) Average Activity Ratio

A

B

C

D

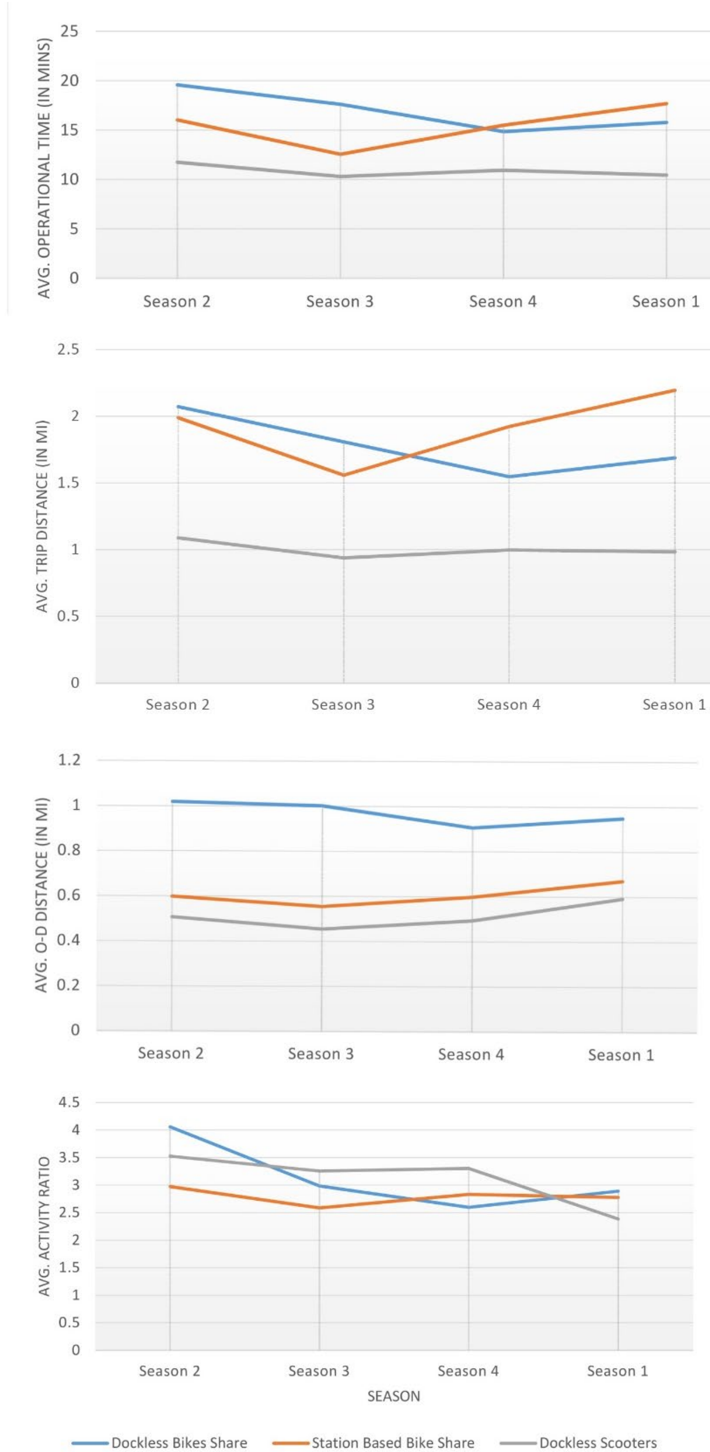

Figure 9: Comparison for Seasons: (A) Average Operational Time, (B) Average Trip Distance, (C) Average O-D Distance, (D) Average Activity Ratio

Analysis of Variance (ANOVA) Results:

One Way Analysis of Variance Test is conducted firstly for overall three modes, considering averages for operation time, reported trip distance, origin-destination distance, and activity ratio, along with post hoc Bonferroni Test, to understand if similarity exists within two individual groups, even if the overall ANOVA results state otherwise. The Results for the ANOVA Tests (Post hoc BONFERRONI Test) are in Appendix C and Appendix D, which includes the P-value indicating the level of statistical significance.

For the ANOVA Test, the null hypothesis is assumed that the three modes are significantly like one another, as all of the three are micromobility modes, working around the similar technological principles, as well as the concept of shared usage. Comparing the overall averages of the operation time, reported trip distance, OD distance and Activity ratio, all ANOVA results indicate a P-value = 0.000, which is less than the assumed $\alpha = 0.05$, which suggest that there exists a statistically significant difference between the groups for all of the attributes mentioned above. This signifies that all three modes overall are significantly different from one another. Only the post hoc Bonferroni test, in the case of the Activity Ratio, shows a P-value = 1.000 between DBS and DSS. This signifies that under a 95% confidence level, both modes are similar, i.e., there exists in the deviation of the original path, when the user takes long-distance trips on these free-floating micromobility modes. This can be because both these modes are unhinged from docking stations and can be picked up and dropped at any location within the service zone, that users tend to explore places, or make stops in between for their convenience before reaching their destination. Another factor that may have an impact on the use is the charge that one incurs while paying for this service. The pay per minute charge seems much less compared to flat 4-dollar charge/hour in case of SBBS, once the rider uses up the free one-hour minutes.

Below, ANOVA test is conducted for individual modes to assess whether significant similarity is present taking into consideration days of the week, season, month, peak vs. off-peak as well as weekday vs. weekend.

DBS:

Testing for the avg. operational time across the different days of the week results in a P-value = 0.000 which is less than the assumed α value = 0.05, but the post hoc Bonferroni Test shows that similarity exists between Sunday and Saturday (P-value = 1.000), Monday and Friday (P-value = 0.180), Tuesday and Wednesday (P-value = 1.000), Tuesday and Thursday (P-value = 0.259) and Wednesday and Thursday (P-value = 0.904).

From the above-mentioned results, we see a similar pattern (also seen previously), that incase of DBS, average operational time for both the days of the weekend tends to be significant under 95% confidence level (higher average operational values during the weekend). Consequently, in the case of the days of the week, Mondays and Fridays are similar, and Tuesday, Wednesday, and Thursday tend to be similar. This result further echoes with the previous result seen in Figure 6 (A) earlier, where average operational time plots are located near one another in case of Mondays and Fridays, and Tuesdays, Wednesdays, and Thursdays. The similarity in the usage between Monday and Friday can be a result of the fact that both are considered to be important days of the week, Monday being the first day of the workweek, which users wait for to get important work done (for example major businesses, offices operate during these times). Similarly, Friday serves as the starting of the weekend, and users may undertake longer average operational time trips for leisure purposes. Tuesdays, Wednesdays, and Thursdays do not seem as important as Monday and Friday; hence they tend to show similar lower average operational time.

Now taking into consideration average reported trip distance in case of DBS across the different months of the study period, for which the P-value between the different months is 0.000, with assumed α value = 0.05. Post hoc Bonferroni test shows that a significant similarity of 95% confidence level is observed between January and February (P-value = 0.356), September and October (P-value = 1.000), and November and December (P-value = 0.842). This result suggests that seasonality affects the distance traveled by DBS users during these months. Since there is no significant similarity between either July and October (used as an example), which further shows that seasons do affect the distance traveled by users, depending upon the weather conditions.

For the OD Distance across the different peak and off-peak times for DBS, the P-value = 0.000, for the assumed α value = 0.005. The post hoc Bonferroni results suggest that significant similarity lies during off-peak hours and evening Peaks (P-value = 0.059) and midday Peak and Evening Peak (P-value = 0.199). In the first scenario, the P-value is close to the assumed α value = 0.05, which may suggest that some trips between those two groups have similar origin-destination distance. Midday peaks and evening peaks are seen to have almost equal average OD distance as observed earlier in Figure 8 (C) (being the least average OD Distance on the graph). This means that the destinations chosen by the riders during these times are shorter and nearby compared to the other times throughout the day.

SBBS:

Conducting ANOVA analysis for SBBS across the days of the week for avg. operation time, resulted in P-value = 0.000, for assumed α value= 0.05. The post hoc Bonferroni analysis reveals that significant similarities exist between Mondays and Thursdays (P-value = 1.000) and Tuesdays and Wednesdays (P-value = 1.000). This result is dissimilar from the results observed in the case of DBS (in the case between Mondays and Thursdays), where it can be understood that Tuesday and Wednesdays being similar have similar reasoning as DBS. The test for average trip distance across the different months during the 8 months, gives a P-value = 0.000 when α value assumed to be 0.05. Post hoc Bonferroni test shows significant similarities existing between January and February (P-value = 0.053, February and July (P-value = 1.000), February and December (P-value = 1.000), July and December (P-value = 1.000) and August and November (P-value = 0.089). In the case of SBBS, similarities between January and February are also seen in DBS, but not for the rest. Usually, it can be assumed that months grouped as seasons, would show similarities (as observed in DBS), but in this case, this doesn't hold. This suggests that in this mode, users' operational time does not depend upon seasons or weather conditions since similarity is observed between months which unlikely have similar weather patterns. Another conclusion can also be made that average operational time depends upon the user's interest in usage. For the average OD distance across all the peak and off-peak times, the overall P-value is equal to 0.000, when α value = 0.05. Post hoc Bonferroni Test suggests that significant similarity exists between midday peak and afternoon peak (P-value = 0.073), which suggests that users tend to choose SBBS to travel to destinations that tend to be similar in distance from the origin, as explained earlier.

DSS:

Calculating the ANOVA results for an average operational time across the day of the week, P-value equals to be 0.000, taking α value = 0.05. Post hoc Bonferroni analysis only finds significant similarity existing between Sundays and Saturdays (P value= 1.000) in this DSS. This result echoes the previous result for DSS, that increased higher average operational time is observed over the weekends, suggesting that users utilize the service for a similar time over the weekends. Trip distance when compared over the study period, yields a P-value = 0.000, assuming α value = 0.05. But post hoc Bonferroni analysis suggests that significant similarity exists between February and September (P value= 1.000), February and October (P value= 1.000), and September and October (P value= 1.000).

Comparison between Three modes:

Subsequently, the ANOVA test for comparing the three modes takes place for different attributes like the season, weekday vs weekend, and peak vs off-peak to understand whether the three modes are completely different from one another or significantly similar, whether one can be used instead of the other. Overall, for all the different types of combinations, P-value = 0.000 is obtained for all of the cases with ANOVA Analysis (within the groups). But post hoc Bonferroni test has given suggestions that similarity exists for some modes even if the ANOVA test is not able to pick up the individual results.

Since all P-values = 0.000, it suggests that overall, all three types of modes are significantly different from one another, i.e. they are not directly comparable. The post hoc Bonferroni results suggest that during Weekdays, the average activity ratio shows a significant similarity between DSS and SBBS (P-value=0.648), which suggests that similar rate of deviation from original path take place during weekdays for longer trips, whereas over the weekend, DBS shows significant similarity with SBBS (P-value = 1.000), both of which was previously observed in Figure 7(D). This suggests that DBS users' behavior is more towards DSS users during the weekdays and shifts towards SBBS during the weekends. This similarity between DBS and SBBS is also seen over the weekend for average operational time (P-value = 0.879) suggesting that both users spend a significantly equal amount of time over the weekend utilizing both modes. Looking at the seasonal variation, DBS and SBBS show similarity in the case of average activity ratio only during Early Spring (P-value = 0.08), which suggests that both DBS and SBBS users deviate from the original destination on longer trips, which is not observed during any of the other seasons. Figure 9(D) previously had suggested similar results with the graph showing average activity ratio values almost close to each other for DBS and SBBS.

When using the ANOVA test for analyzing the different peak and off-peak times, all subsequent P-values = 0.000 were observed, when α value = 0.05 is taken. Post hoc Bonferroni analysis suggests that in the case of morning and evening peak times, all the three modes are significantly dissimilar in behavior, i.e. none of the individual comparisons shows a P>0.05. But the post hoc Bonferroni results suggest that significant similarities exist between the modes for midday peak time, evening peak time as well as for off-peak times in case of average activity ratio. In the case of midday peak time, SBBS and DSS show significant similarity (P-value= 1.000) and for evening peak time, only SBBS tends to be like either of the other two modes. DBS and SBBS (P-value = 0.883), SBBS and DSS (P-value = 0.423). Now one of the reasons for this result is the fact that DBS usage is restricted within the pilot project area, whereas the SBBS docking stations are located within downtown and as well as spread near UT Austin as well as south of the river. Similarly, in the case of DSS, other than the pilot zone, the usage zone is far more expansive than SBBS. So, we do get to see SBBS acting like the common link between the two, such that some of the trips show similarities towards DBS and some trips like DSS. At the same time, it is also observed that reported average trip distance for evening peak is similar for DBS and SBBS (P-value = 1.000) and average O-D distance is similar between SBBS and DSS (P-value = 1.000). In the case of off-peak times, both free-floating modes are similar (P-value = 1.000), which can signify that the rate of deviation from their destinations is similar.

After conducting ANOVA tests for the individual modes and comparing the three modes taking into consideration a two-hour time limit, it is seen that individually all three modes have few similarities across the day of the week, months, seasons, as well as peak times, but overall differ significantly. The average activity ratio is found to be the most common attribute amongst all three modes displaying significant similarities, not necessarily found in all three micromobility modes compared across the same time frame. This is because since the user has the flexibility of movement, even though time and money can act as constraints, users have the freedom to deviate from their original destinations and conduct other activities on their way. This flexibility is not provided in case of public transit, where the route is fixed. Similarly, as McKenzie (2018) points out, different modes have varying average time when comparing docked and dockless bike share, which is one of the reasons why similarity may not be observed for the overall average time a user spends on these modes. During the weekend, the data shows that DBS and SBBS have similar behavior towards time traveled. This can be because users may utilize both modes for similar purposes. Since it is observed that, spatially, both DBS and SBBS are somewhat concentrated around the same areas, it can be assumed that the purpose of these trips may be similar compared to the trips during the week. Both types of users travel for the same time but reported trip distance is different. Now assuming both types of users are traveling to the same location, the time needed to find a docking station to unlock/ lock bicycles would be more in comparison to DBS, where bicycles can be locked/unlocked anywhere. But at the same time, SBBS is concentrated in and around the urban core whereas DBS has the flexibility for users to start and end trips outside the CBD, hence it is not sure whether DBS is becoming a competition for SBBS. In Early Spring, it is observed that the DBS and SBBS Activity Ratio is similar. According to Younes et al (2020), dockless mobility is less sensitive to weather changes than SBBS especially humidity and rain. But in this case, it is observed that users tend to, for both mobilities, spend proportionally similar distances deviating from their destinations, which can be assumed that bicycle users enjoy the cold weather and roam around more in comparison to DSS. So, the effects may be dissimilar during other seasons, but similar during the early spring period. Peak times observes similarities between two modes, but mostly for Activity Ratio. During Midday Peak SBBS and DSS shows similarity. According to Mathew et al (2019), DSS trip usage starts after 11 AM. Based on the SBBS data, high concentrations of trips are also generated between 11 AM to 1 PM. Since the majority of the trips are concentrated in and around similar areas, it can be assumed that both serve similar user groups, be it students going to class at UT or other recreational purposes such as grabbing lunch. During Evening Peak time, DBS shows similarity with SBBS in terms of average trip distance users travel and with DSS for destination distance chosen. This means that for longer trips located beyond a block, dockless users tend to deviate at a similar range from their destinations, but at the same time travels similar distances to SBBS, which means that normal travel distances between DBS and SBBS may or may not be same, depending on the time taken for SBBS users to find an available docking station, as explained by McKenzie (2019). Off-peak time shows similarity in Activity Ratio between DBS and DSS, which can account for the flexibility of the modes being unhinged, such that users can leave their vehicles wherever convenient within the operating zone, in comparison to fixed docking stations which are mostly located in and around the CBD, which limits the trips within boundaries. Overall only DBS and DSS show significant similarity towards average activity ratio while comparing the different temporal attributes, and this reasoning can be assumed due to similar technologies being employed in making these systems free-floating, as assumed by Jiao and Bai (2020).

COMPARISON BETWEEN THE TWO BIKESHARE MODES:

The previous analysis includes the three micromobility options, where subsets of the original DBS and SBBS dataset are used as DSS only included trips within 2 hours (as that was the maximum battery life for scooters before they needed to be charged). So, to make the datasets of DBS and SBBS, which contained trips within 24 hours, comparable with scooters, a subset of trips with a maximum operation time of 2 hours was used. In this section, both the original datasets for DBS and SBBS are used to compare longer trips occurring within 24 hours, which are not included in the previous analysis. Descriptive Statistics for the 24 hour data for SBBS and DBS are located in Appendix E.

Comparing the trips of DBS and SBBS, across the different days of the week, in Figure 10 (A), it is observed that the average operational time for SBBS overall is much longer than DBS. An opposite scenario is seen previously when trips times are bounded within 2 hours. The average operational time for increase by more at least 15 mins over Saturdays and Sundays, and 7-10 mins during the weekdays for SBBS. A slight increase of 3-4 mins is observed on Saturdays and Sundays, and 2-3 mins on the weekdays for DBS. The average operational time trend for both are not similar, especially during the weekdays, where SBBS users travel the least number of minutes on Thursdays and DBS on Tuesdays, signifying that user behavior changes during the week for both the modes. In Figure 10 (B), it is observed that reported average distance for DBBS is higher on the weekends (Saturdays and Sundays) increasing by more than 2 miles when compared with the previous dataset. For DBS users, the average distance traveled stays almost similar throughout the week, slightly decreasing during the weekdays, but not significantly. When comparing the average OD Distance for the two modes (Figure 10 (C)), is seen that the destinations chosen by SBBS users are much shorter than those of DBS. In fact, for SBBS, it is higher during the Saturdays and Sundays, and lower during the weekdays. In the case of DBS, it is the opposite, with users choosing a destination that is much more distant than those chose during the weekdays. For Average activity ratio observed throughout the days of the week for longer trips (trips where displacement is more than 0, i.e. origin and destination are not the same point, or within the same block), SBBS users tend to deviate around 8 times during the weekend, compared to the weekdays, where least deviation is 4 times of the origin destination distance (Figure 10 (D).

Just as observed earlier, in Figure 11 (A) the average operational time for both DBS and SBBS increases over the weekends, more for SBBS than DBS. Similarly, in Figure 11 (B), the average reported trip distance is also seen to increase for both the modes over the weekend than on weekdays. For the average O-D distance, it is seen (in Figure 11 (C)) as previously, that the chosen destination distances decrease over the weekends compared to the weekdays for DBS and is opposite in the case of SBBS. For longer trips, the average activity ratio increases slightly over the weekend in the case of DBS users, and significantly for SBBS users.

A

B

C

D

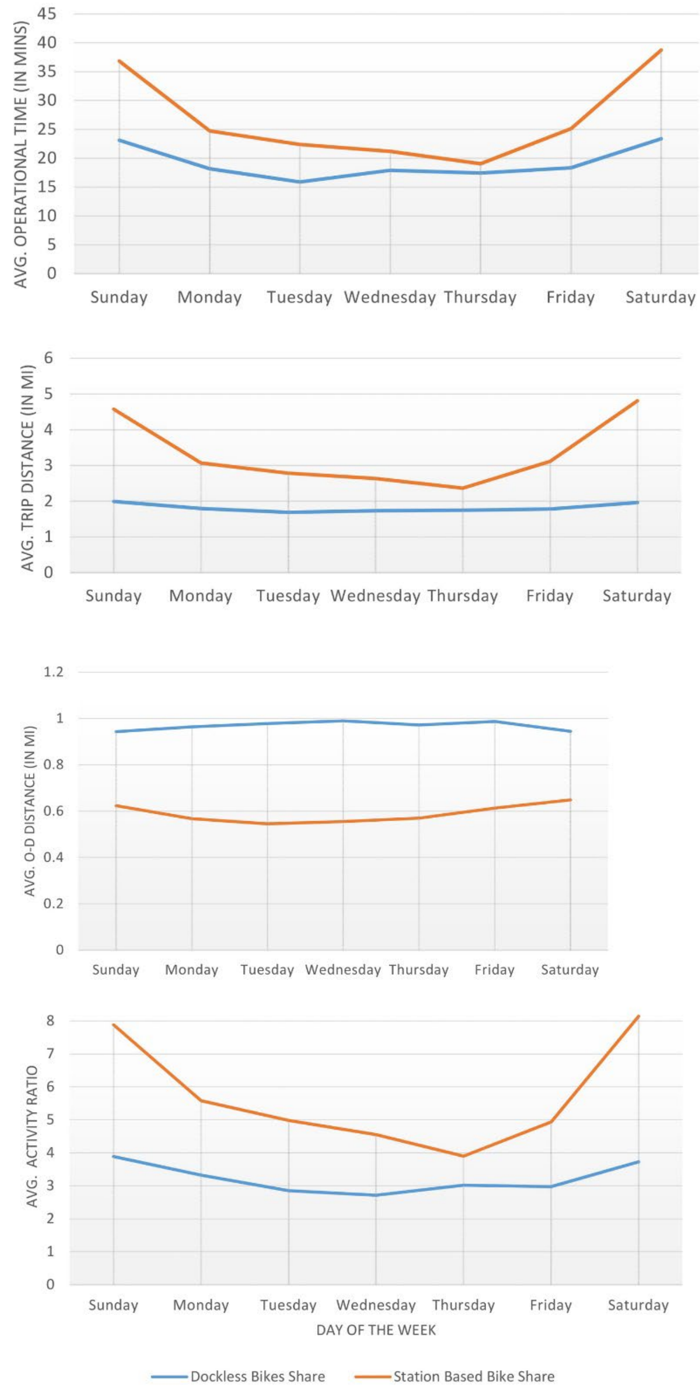

Figure 10: Comparison for Day of the Week: (A) Average Operational Time, (B) Average Trip Distance, (C) Average O-D Distance, (D) Average Activity Ratio

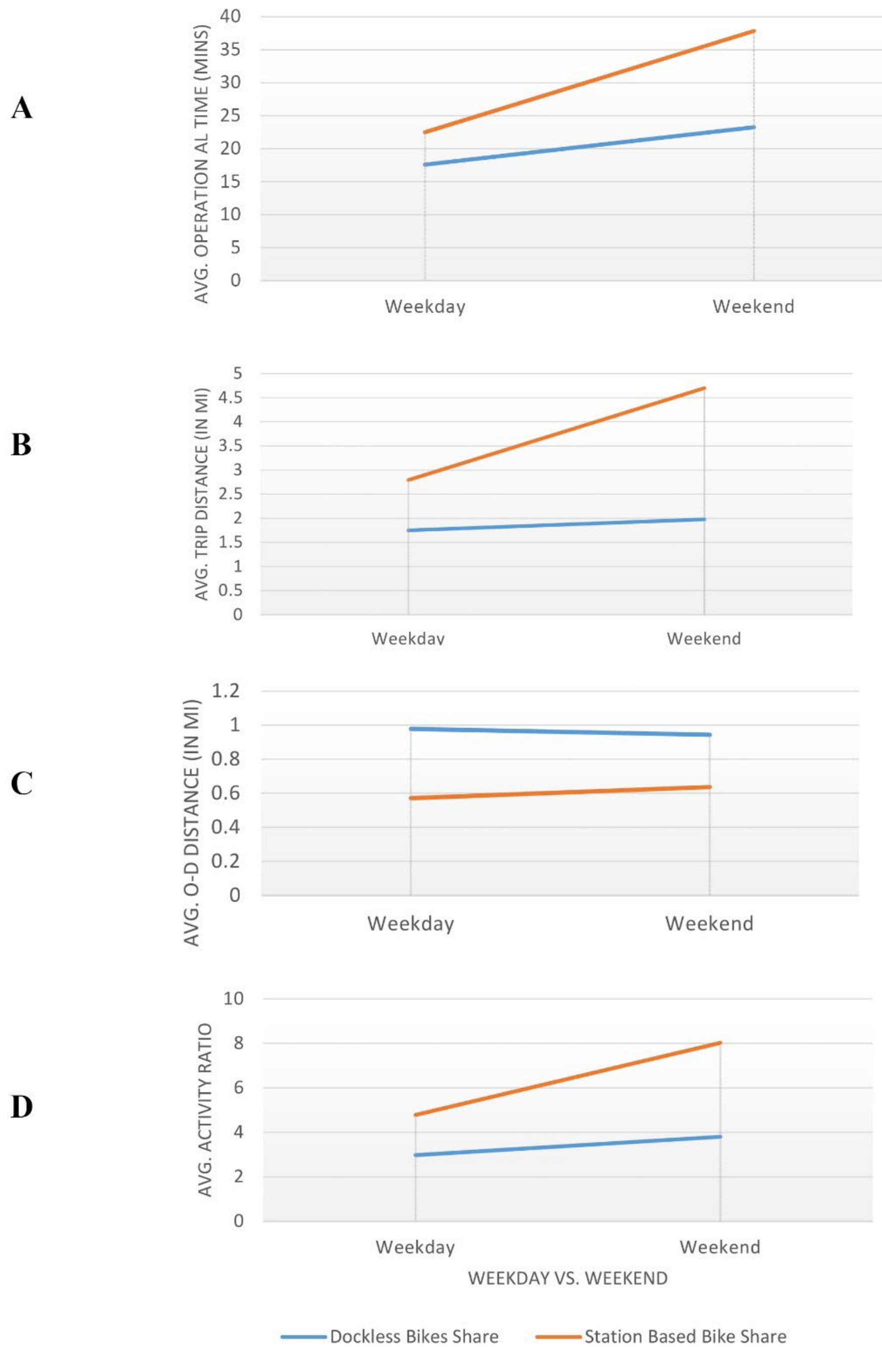

Figure 11: Comparison for Weekend vs Weekday: (A) Average Operational Time, (B) Average Trip Distance, (C) Average O-D Distance, (D) Average Activity Ratio

Analyzing the peak and off-peak times for both DBS and SBBS, the highest average operational time for SBBS is seen during evening peaks (Figure 12(A)), whereas for DBS, it occurs during the midday peak. At the same time, both modes show the least average operational time during the morning peak, which corresponds to the least average trip distance observed in Figure 12(B) for the same period. This trend had also observed previously when all three modes were compared, signifying that during the morning peaks, both types of users travel the least distance taking the least time. Even though the highest average operational time for DBS occurs during the midday peak, the average trip distance across the different peaks are almost the same. This can signify that users may deviate from their original destination or have stopped in between their trips for other activities. This assumption can be further established when the O-D average distance is viewed across the different peaks (Figure 12(C)). The average O-D distance during midday peak is the lowest, which signifies that riders have deviated from their destination path, approximately 4 times. The average O-D distance for SBBS is similar throughout the peak times and off-peak times, but the increased average distance during evening peak signifies the increase in deviation or users using the time to do other activities. For SBBS, maximum deviation is observed during the evening peak, almost 7.5 times the O-D distance as observed in Figure 12(D). Due to the difference in choice of average O-D distance across the day, shows a variation in the deviation of the path for DBS during the different peak and off-peak times.

A

B

C

D

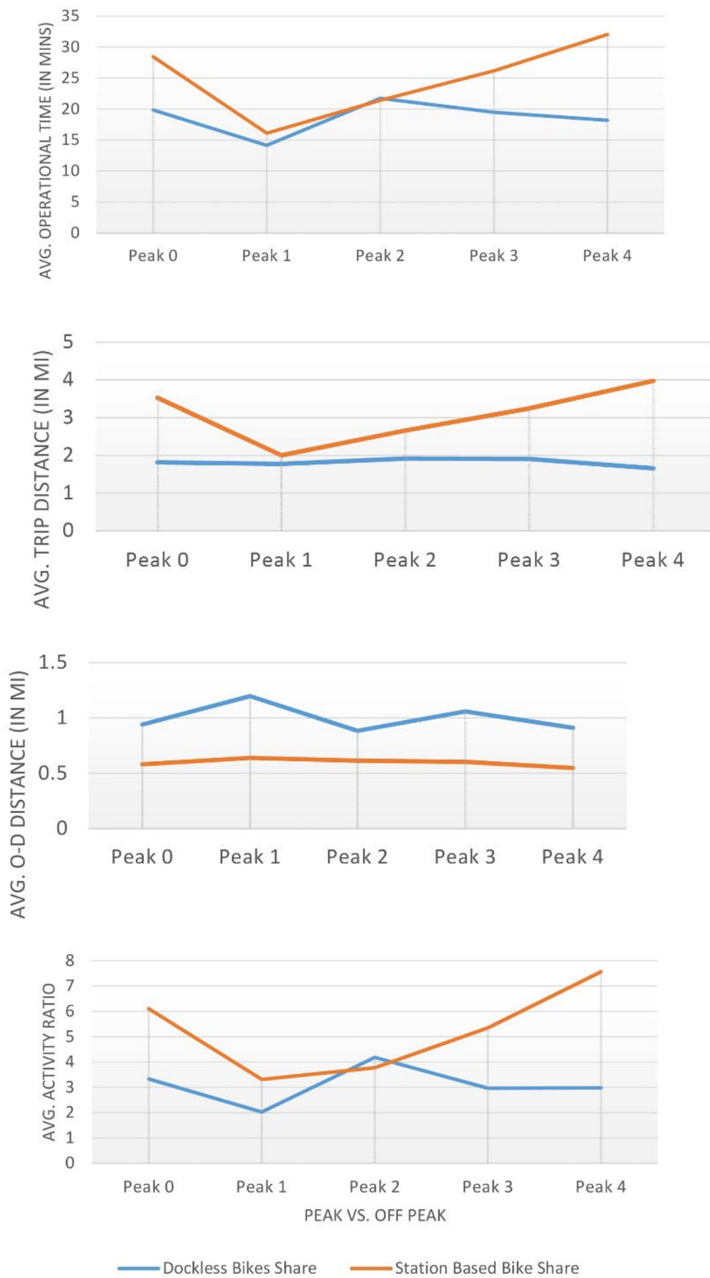

Figure 12: Comparison for Daily Peaks: (A) Average Operational Time, (B) Average Trip Distance, (C) Average O-D Distance, (D) Average Activity Ratio

In the case of the different seasons, it is observed that the highest average operational time for SBBS is highest during Early Spring (Figure 13 (A)), whereas in the case of DBS it is during Summer when the free-floating bikes were first introduced. Lower operational time in the case of SBBS is observed during the fall for SBBS. Generally, it has been found out that weather plays an important role in assessing the time cyclists spend on trips. This observation coincides with previous literature. At the same time reported average trip distance is greater in the case of SBBS (Figure 13 (B)) during Early Spring, which further echoes the previously made claim. For DBS, the highest average trip distance is July (Summer), which can account for the initial craze Austinites may have faced with the introduction of the new mobility service.

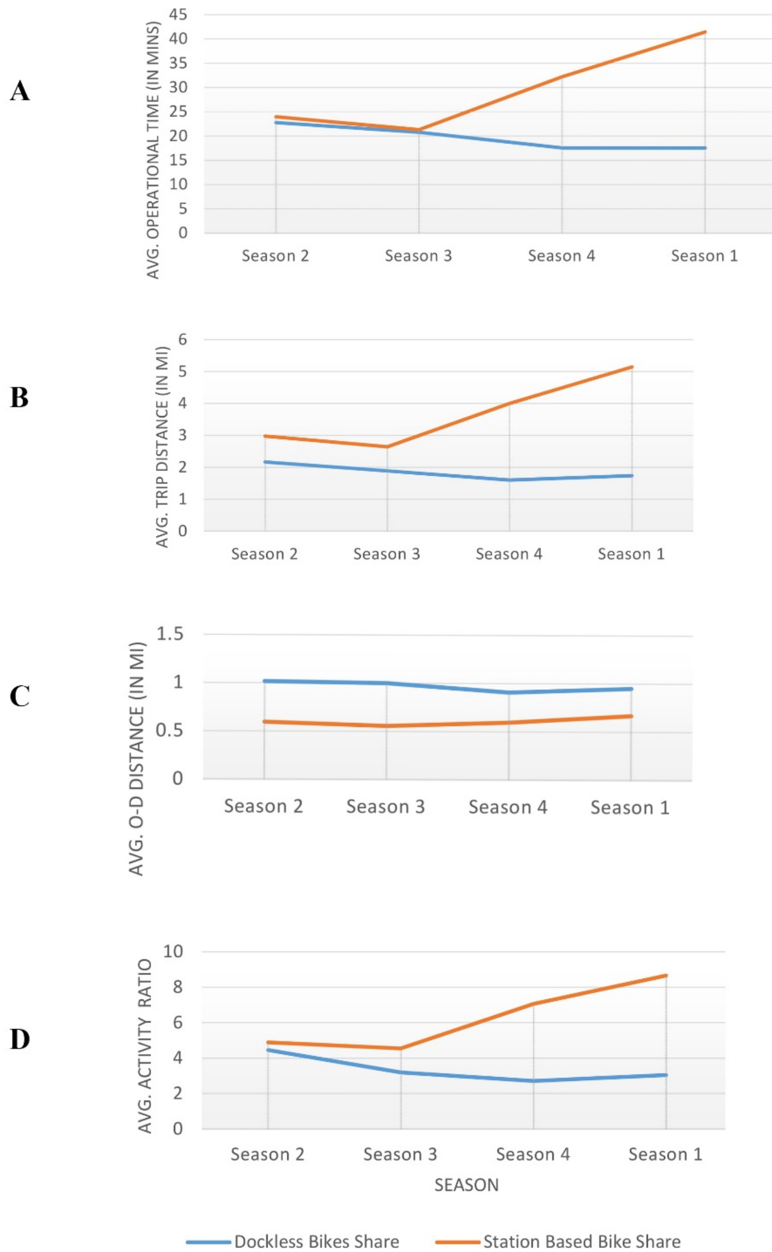

Figure 13: Comparison for Seasons: (A) Average Operational Time, (B) Average Trip Distance, (C) Average O-D Distance, (D) Average Activity Ratio

Two-Sample T-Test of Means Analysis of the two modes:

In this section, Two-Sample T-Test of Means Analysis is conducted between the two bike-share modes, taking into consideration averages of the operation time, reported trip distance, origin-destination distance, and activity ratio, to determine whether significant similarity exists (if at all) between the two modes for trips with an operational time of 1 day. T-Tests uses the three attributes and variations of weekdays vs weekends, peak times vs. off-peak times and seasons, results of which are in Appendix F and includes the P-value indicating the level of statistical significance.

After conducting the Two-Sample T-Test of Means, it is observed that the majority of the results for each pair using the different attributes give P-value < 0.05, where α value = 0.05 is taken for a 95% confidence level. This signifies that both modes, when compared for trips within 24 hours, are statistically significant in most of the categories. But it is observed for two tests, that P-value > 0.05. This occurs for the average operational time during midday peak (P-value= 0.5615), suggesting that both mode users spend somewhat equal amounts of time using the modes for their trip, during the midday. It is also observed that, when looking across seasonal variation, both modes are significantly similar during winter (P-value = 0.274). But in all other cases, results obtained showed that when comparing the two modes, they are significantly dissimilar.

Now for trips more than 24 hours, similar results are observed for Midday peak time, when users spend an equal amount of time on DBS and SBBS systems, with an average time of 21 minutes, much longer compared to the average time observed during the 2-hour window of analysis. In the case of the ANOVA results, similarities with DSS are observed. But in this scenario, DBS behaves differently, more like SBBS in terms of distance traveled by users. At the same time, a similarity is seen during Winter when both modes spend almost equal times in the cold pleasant weather.

From both the ANOVA and T-Test Results it is understood that behavior-wise, all three modes show some similarities when compared under the two-hour window. But, when trips become more than two hours, modes are not comparable and give dissimilar results. At the same time, when trips of these three micromobility modes are observed spatially, it is seen that, more or less, they tend to be concentrated in and around the same locations. Due to the variation in trips, at first, it may seem that one mobility mode is catering over a wider area in comparison to the other, it is difficult to understand which categories of users the mobility modes are targeting. But when each type of mobility mode is looked at individually, and dot density counts are catered based on individual counts, and not dependent on other modes, readers can observe a clarity in key locations. And in doing so, it is observed that all three modes concentrate on the locations of southern Downtown, The University of Texas at Austin, and the West Campus. These locations are key locations according to the operating modes as according to previous studies in free-floating micromobility modes suggests that it flourishes in urban centers and is popular amongst the younger individuals with low incomes as well as students, in comparison to SBBS (Li et al, 2019). In the Austin scenario, it is seen that students contribute to a larger share (66.7%) in the SBBS user group in comparison to normal members or casual riders. And locations of SBBS origins and destinations are concentrated maximum in and around The University of Texas at Austin and West Campus, in comparison to the docking stations at Downtown. It is also observed that multiple stations other than the ones mentioned above, do not even generate or attract trips, whereas those same locations produce a lot of free-floating traffic during the same period.

So clearly these observations help us to understand that even though micromobility may target similar users, and be concentrated in and around the same spatial geography, they show less similarity when being compared in terms of average time spent on these modes, miles traveled or distance of destinations chosen. The only similarity which may come up in this comparison is the amount of deviation each type of micromobility user may incur while traveling from one location to another, signifying that for other activities, traffic, longer routes may affect their mode of travel.

Chapter 6: Recommendation and Conclusion

Now, from the above results and analysis, it is necessary to touch base and evaluate the answers derived from the above study based on the initial questions asked. It is observed that all three micromobility modes showed variation depending upon the different temporal characteristics like the day of the week, weekend vs weekday, peak vs off-peak times, and seasons in terms of trip volume, average trip distance and average distance traveled. It is seen that trip volume-wise, all types of micromobility mode show higher volume as the week progresses towards the weekend, with maximum trips observed on Saturday (for the free-floating type) and Friday for SBBS, contradicting to Zamir et al's (2019) observation that DBS volume does not significantly increase over the weekends. In contrast to Jiao and Bai (2020), DSS observed higher average trip time and the average reported distance traveled over the weekend than weekdays. Now when comparing average time traveled by the three micromobility modes taking into the 2-hour window for comparison, DSS has the least average time-traveled of 10.76 mins, then SBBS of 14.73 mins and then DBS of 16.76 mins. But when the two-hour window is not taken into consideration, then SBBS significantly increases to 26.78 mins and DBS to 19.45 mins, changing the initial trend. One of the major reasons which result in this change can be due to the full utilization of the special weekend or three day passes for SBBS. This is echoed with the increase in the average trip distance between SBBS and DBS for the 24-hour window, in comparison to the 2-hour window, where average trip distance increases almost more than 1.5 times.

Spatially visualizing the trips, it is observed that for all the three types of micromobility modes, maximum usage takes place around southern Downtown, where the majority of the dining/recreational places are located, The University of Austin and West Campus, where the majority of the students are found. It is already established previously that micromobility modes tend to be popular amongst the younger low-income population, students. Hence it was not a surprise to find this observation prevalent for all three types of modes. Even though DSS, because of its high usage is used widely across the CBD, because of its usage flexibility, similar observations were not observed for DBS or SBBS. SBBS users were concentrated around the docking stations, but in the case of DBS, the concentration across the CBD can account for the low fleet size, and hence non-availability for usage. Other locations near the riverfront as well as East Riverside, and South Congress served as common areas where trips were concentrated, but the variation differed based on the docking locations and fleet size of the free-floating micromobility mode.

From the results, it is also evident that in most cases, the ANOVA results for the three micromobility modes concludes the fact that DBS, SBBS, and DSS overall are dissimilar to each other, in terms of the average user operation time, average user trip distance, destination choice made or simply the rate at which users can deviate from their original path. Even though they cater to the public, the way each user utilizes them is different, i.e. the services complement and not compete. Now in terms of understanding whether the University of Texas at Austin affects the usage, then definitely that is proven when common usage patterns/ concentrations are observed for all the three types of micromobility across the university campus and West Campus, where a majority of the students study and reside. At the same time, SBBS records the highest bike share usage near Speedway and PCL (UT Library), along with residential locations on West Campus. The University of Texas Student and Staff pass accounts for 66.7% of the total SBBS trips observed during the 8-month study period, hence it is obvious that the university does have a significant impact on the micromobility usage in Austin

All three have different travel times and operate over similar and different areas in the city. DBS is restricted within the CBD as an operational zone as well as near the University of Texas, West Campus, whereas for SBBS, the stations are a bit more scattered, mostly concentrated in the CBD, along with a few near/ at the University of Texas at Austin and near the Colorado River, to encourage young minds and other public to utilize the infrastructure provided, thereby encouraging many common city goals, like lowering congestion, reducing pollution as well and promoting health awareness. The locations of the SBBS near parks and on the Austin-Boardwalk are deliberately made to encourage users to ride bike share for recreational purposes. But the issue lies in the fact that stations are not very well placed, especially in East Austin and withing the CBD, where even though nil trips are being generated or attracted, DBS and DSS specifically have higher trips being generated in the same locality. A user cannot utilize this mode if relevant stations are not present near the vicinity of their destinations. Since the SBBS users tend to be hinged at fixed locations. But that is where the concepts of free-floating bike share or e scooter-share comes in. When the operational areas for all three modes for Austin are analyzed, it is observed that all three modes have a common location as operation areas, after which they branch out and that is Austin downtown, where originally permit was given to the free-floating modes to start operating as per the Pilot Program launched in summer 2018. Separate e scooter operators have paid the city to include extra licenses to expand their services to outlying areas. This is the reason why e scooters are seen to be used at a higher rate than SBBS or DBS service, due to their restricted fleet size and operational areas. Hence in areas where bike share is not available, are the places where which would utilize e scooter-share over bike share. Free-floating modes provide a lot of user flexibility especially not having to find stations and lock bikes after each trip, which takes away a lot of time from the user's hands.

The city can expand the public-funded bike share system and locate stations at popular destinations other than the urban core, especially along corridors where free-floating systems generate and attract significant traffic. Looking into the SBBS data for membership attributes, came with the conclusion that the majority of the members are students and Staff from UT Austin, who utilize the service at a subsidiary cost. Similar services can be provided to the other institutions located in the city, as it proves that the service is popular amongst the students and staff, providing a low-cost transportation mode. Similarly, City needs to analyze the data for locational factors for establishing docking stations, as well as the number of docking units depending on the demand for the location. There may be locational issues that may stop encouraging the use of SBBS at certain stations in comparison to the others.

But expanding over these particular locations and other relevant popular areas that have the potential to generate a user base requires a lot of initial infrastructure costs from the city, from establishing docking stations, providing vehicles that may slow down the process significantly. Free-floating modes like bike share and e scooter-share are operated by private organizations, who pay the city license fee to operate their vehicles in certain areas. The city has a count of fleet size and has provided certain laws and rules that these operators and users should abide by, to control the regulation of these vehicles and services. The initial cost of introducing the free-floating service is much lower in comparison to establishing a new station. But maintenance wise, free-floating service costs more, as the operators must employ people to pick up and charge the vehicles for use. But since private operators have already established a system that goes and picks up vehicles to charge, then it should not be a problem to maintain a larger fleet size, since more and more users will utilize their services. Even though free-floating modes seem convenient, there is no guarantee that vehicles are always distributed equally over the operational areas, mostly depending on users who end their trips and locations which are inconvenient or far off from others. The probability of knowing that vehicles are nearby is much more in case of a station-based bike share. So, the city cannot rule out one over the other. Since the initial cost of establishing stations requires a lot of economic infrastructures, the city can hand over the bike share services to private operators, who utilize their resources in further enhancing and expanding the service. At the same time, the city can regulate these services by establishing an operator fee, similar to the free-floating service and restrict and regulate the operational area and service provided.

LIMITATIONS OF RESEARCH:

Researchers have utilized the Origin and Destination locations for analyzing network pattern differences using exact coordinates that are available in their respective data sets. Since the dockless mobility data set for Austin does not include exact coordinates (but trips were binned into hexagons, to preserve the anonymity of its users), this opportunity cannot be utilized. Many researchers have used tessellations to provide service areas/ similar spatial resolutions using docking stations as centers. But in this research, this method cannot be used, as the stations are concentrated in and around the downtown area of the city and are not widely dispersed. Using a common spatial resolution is tough, for these three types of mobility options, since even the smallest geographical unit, i.e. census block groups will not be able to do justice in locating the origins and destinations, since, for dockless mobility, the coordinates are not exact. At the same time, binning the location of trips to block groups will not provide researchers the exact locations where these trips were generated and attracted. But since the locations for dockless mobility can range within a block based on the coordinates provided, census block can be used to somewhat visualize the trip data to estimate the concentrations of trips.

Appendices

Appendix A (Trip Volume for the Three Micromobility Modes)

Dockless Bike Share (DBS)							
Hour ID	**Sunday**	**Monday**	**Tuesday**	**Wednesday**	**Thursday**	**Friday**	**Saturday**
0	571	215	164	234	233	324	521
1	495	123	125	131	152	212	394
2	460	78	65	86	101	152	411
3	165	41	17	40	58	81	129
4	68	28	30	21	27	60	69
5	50	26	36	52	36	47	39
6	66	68	82	85	102	93	33
7	84	251	323	290	319	270	95
8	173	682	769	827	806	738	220
9	337	569	619	667	723	648	381
10	580	521	498	553	569	555	658
11	902	646	490	557	590	683	885
12	1082	710	681	671	756	924	1126
13	1166	715	656	664	678	885	1231
14	1243	735	654	662	731	843	1358
15	1358	760	693	670	820	1021	1428
16	1271	883	880	855	918	1141	1326
17	1097	1147	1167	1210	1368	1304	1264
18	876	857	956	927	1021	1035	1124
19	726	648	754	682	794	810	979
20	617	515	585	634	672	698	792
21	495	453	547	557	618	790	795
22	439	382	463	476	492	750	806
23	354	257	325	349	416	675	704
Total	**14675**	**11310**	**11579**	**11900**	**13000**	**14739**	**16768**

Table 9: Trip Volume for DBS

Station Based Bike Share (SBBS)							
Hour ID	**Sunday**	**Monday**	**Tuesday**	**Wednesday**	**Thursday**	**Friday**	**Saturday**
0	534	323	248	290	316	369	423
1	469	227	161	152	195	258	358

2	306	110	102	90	89	140	310
3	116	54	42	41	45	57	117
4	51	22	20	21	26	28	41
5	32	60	83	98	75	78	37
6	59	148	170	156	171	134	46
7	89	420	617	615	686	486	129
8	272	906	851	1033	830	983	355
9	525	1096	1031	1042	1056	1049	650
10	906	1027	1039	1024	1268	1142	1023
11	1143	1393	1055	1323	1110	1584	1465
12	1689	1562	1499	1358	1589	1721	1855
13	1644	1576	1405	1398	1654	1713	1963
14	1588	1413	1159	1305	1316	1709	1914
15	1567	1551	1735	1433	1822	1754	1803
16	1494	1597	1691	1608	1729	1779	1733
17	1447	1849	1902	1833	1886	1785	1648
18	1495	1645	1789	1658	1825	1570	1566
19	1389	1349	1473	1427	1484	1309	1325
20	1129	1186	1171	1187	1273	1109	1230
21	907	875	981	1036	1028	1086	1134
22	774	677	742	810	902	950	977
23	467	494	533	525	595	605	713
Total	**20092**	**21560**	**21499**	**21463**	**22970**	**23398**	**22815**

Table 10: Trip Volume for SBBS

Dockless Scooter Share (DSS)							
Hour ID	**Sunday**	**Monday**	**Tuesday**	**Wednesday**	**Thursday**	**Friday**	**Saturday**
0	4581	2179	2095	2198	2459	2745	4459
1	3601	1227	1443	1420	1529	1966	3509
2	3423	846	1032	920	1087	1642	3221
3	1626	422	451	410	451	752	1389
4	851	318	326	342	363	481	691
5	532	699	859	828	847	810	536
6	860	1522	1821	1861	1896	1763	771
7	1632	5846	7245	7281	7569	5998	1830
8	3746	12062	12881	14090	13525	13039	4307
9	7716	13298	15201	14314	16736	13323	8084

10	13719	13796	12612	13332	14436	14995	14283
11	20797	17703	15615	17536	17989	22052	20677
12	26214	22823	23107	21947	26445	27570	27761
13	29122	21889	20481	20361	24180	27118	32317
14	30156	21643	18555	19200	21866	25945	34452
15	29955	20843	21737	19588	24679	25975	35578
16	27752	21631	21892	20069	23846	26520	34870
17	25218	24836	26457	24217	27744	27412	32182
18	21301	20225	23070	22264	24170	24632	28048
19	18385	16328	19850	19002	20877	20913	24093
20	14322	14115	17049	16469	18582	19724	19877
21	7557	7521	8563	9173	10447	11822	11168
22	4498	4889	5146	5672	6381	8013	7642
23	3160	3453	3340	3663	4589	6403	6422
Total	**300724**	**270114**	**280828**	**276157**	**312693**	**331613**	**358167**

Table 11: Trip Volume for DSS

APPENDIX B (DESCRIPTIVE STATISTICS FOR COMPARING THE THREE MICROMOBILITY MODES)

Table 12: Over All Three Modes

Dockless Bike Share (DBS)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	92,894	16.77	17.11	0.02	120.00
Trip Distance	92,894	1.75	1.62	0.00	81.26
O-D Distance	92,894	0.97	0.80	0.00	23.28

Station Based Bike Share (SBBS)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	149,674	14.73	17.89	2.00	120.00
Trip Distance	149,674	1.83	2.22	0.25	14.90
O-D Distance	149,674	0.59	0.47	0.00	5.13

Dockless Scooter Share (DSS)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	2,130,296	10.76	11.37	0.20	120.00
Trip Distance	2,130,296	0.99	0.96	0.05	19.04
O-D Distance	2,130,296	0.51	0.49	0.00	15.11

Table 13: By Day of the Week

Dockless Bike Share (DBS)					
Day of Week = 0 (Sunday)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	14,475	19.86	19.14	0.07	120.00
Trip Distance	14,475	1.91	1.77	0.00	36.84
O-D Distance	14,475	0.94	0.80	0.00	9.92
Activity Ratio	13,622	3.67	10.58	0.00	432.82
Day of Week = 1 (Monday)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	11,183	15.67	16.22	0.02	120.00
Trip Distance	11,183	1.73	1.73	0.00	81.26
O-D Distance	11,183	0.96	0.79	0.00	10.11
Activity Ratio	10,721	3.15	9.61	0.00	360.20
Day of Week = 2 (Tuesday)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	1,507	14.43	15.02	0.02	119.73

Trip Distance	1,507	1.65	1.48	0.00	16.71
O-D Distance	1,507	0.98	0.82	0.00	15.99
Activity Ratio	11,012	2.77	8.32	0.00	214.01
Day of Week = 3 (Wednesday)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	11,762	14.54	15.01	0.03	119.82
Trip Distance	11,762	1.67	1.48	0.00	21.23
O-D Distance	11,762	0.99	0.81	0.00	9.09
Activity Ratio	11,269	2.57	6.64	0.00	164.86
Day of Week = 4 (Thursday)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	12,868	14.97	15.68	0.05	118.52
Trip Distance	12,868	1.68	1.51	0.00	17.81
O-D Distance	12,868	0.97	0.77	0.00	8.11
Activity Ratio	12,334	2.84	8.46	0.00	203.81
Day of Week = 5 (Friday)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	14,569	16.23	16.33	0.03	119.82
Trip Distance	14,569	1.72	1.53	0.00	23.64
O-D Distance	14,569	0.99	0.83	0.00	23.28
Activity Ratio	13,935	2.73	7.40	0.00	256.52
Day of Week = 6 (Saturday)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	16,530	19.88	19.32	0.03	119.97
Trip Distance	16,530	1.86	1.75	0.00	24.97
O-D Distance	16,530	0.94	0.80	0.00	11.23
Activity Ratio	15,533	3.42	9.51	0.00	200.39

Station Based Bike Share (SBBS)					
Day of Week = 0 (Sunday)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	19,255	18.92	20.49	2.00	120.00
Trip Distance	19,255	2.35	2.54	0.25	14.90
O-D Distance	19,255	0.63	0.56	0.00	4.53
Activity Ratio	16,590	3.38	6.41	0.49	132.66
Day of Week = 1 (Monday)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	21,059	12.95	16.41	2.00	120.00
Trip Distance	21,059	1.61	2.04	0.25	14.90
O-D Distance	21,059	0.57	0.44	0.00	4.53

Activity Ratio	19,366	2.51	4.32	0.54	122.87
Day of Week = 2 (Tuesday)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	21,028	11.68	14.97	2.00	120.00
Trip Distance	21,028	1.45	1.86	0.25	14.90
O-D Distance	21,028	0.55	0.40	0.00	5.13
Activity Ratio	19,457	2.39	4.28	0.46	113.28
Day of Week = 3 (Wednesday)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	21,037	11.57	15.01	2.00	120.00
Trip Distance	21,037	1.44	1.86	0.25	14.90
O-D Distance	21,037	0.55	0.41	0.00	4.79
Activity Ratio	19,569	2.38	4.88	0.52	161.62
Day of Week = 4 (Thursday)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	22,580	12.71	15.88	2.00	120.00
Trip Distance	22,580	1.58	1.97	0.25	14.90
O-D Distance	22,580	0.57	0.43	0.00	5.13
Activity Ratio	20,786	2.44	4.36	0.50	131.87
Day of Week = 5 (Friday)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	22,832	15.07	17.97	2.00	120.00
Trip Distance	22,832	1.87	2.23	0.25	14.90
O-D Distance	22,832	0.61	0.48	0.00	3.74
Activity Ratio	20,865	2.74	4.76	0.50	125.49
Day of Week = 6 (Saturday)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	21,883	20.50	21.40	2.00	120.00
Trip Distance	21,883	2.54	2.66	0.25	14.90
O-D Distance	21,883	0.65	0.56	0.00	3.86
Activity Ratio	18,841	3.64	6.73	0.53	145.23

Dockless Scooter Share (DSS)					
Day of Week = 0 (Sunday)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	300,724	13.54	13.58	0.20	119.95
Trip Distance	300,724	1.18	1.11	0.05	16.34
O-D Distance	300,724	0.53	0.52	0.00	15.06
Activity Ratio	281,325	3.80	6.97	0.01	221.09

Day of Week = 1 (Monday)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	270,114	9.98	11.01	0.23	120.00
Trip Distance	270,114	0.95	0.93	0.05	16.67
O-D Distance	270,114	0.51	0.48	0.00	13.68
Activity Ratio	255,911	2.90	5.51	0.01	189.23
Day of Week = 2 (Tuesday)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	280,828	8.93	9.61	0.23	119.92
Trip Distance	280,828	0.88	0.86	0.05	17.15
O-D Distance	280,828	0.49	0.47	0.00	13.47
Activity Ratio	266,565	2.71	5.06	0.02	180.00
Day of Week = 3 (Wednesday)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	276,157	8.64	9.07	0.22	120.00
Trip Distance	276,157	0.86	0.83	0.05	16.03
O-D Distance	276,157	0.50	0.47	0.00	9.81
Activity Ratio	262,918	2.58	4.63	0.02	175.85
Day of Week = 4 (Thursday)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	312,693	9.27	9.90	0.23	120.00
Trip Distance	312,693	0.90	0.87	0.05	15.84
O-D Distance	312,693	0.50	0.47	0.00	12.21
Activity Ratio	296,852	2.75	5.06	0.02	185.29
Day of Week = 5 (Friday)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	331,613	10.56	10.80	0.22	119.83
Trip Distance	331,613	0.97	0.93	0.05	17.67
O-D Distance	331,613	0.52	0.50	0.00	15.11
Activity Ratio	313,772	2.93	5.31	0.02	211.13
Day of Week = 6 (Saturday)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	358,167	13.58	13.06	0.23	120.00
Trip Distance	358,167	1.16	1.06	0.05	19.04
O-D Distance	358,167	0.54	0.52	0.00	11.86
Activity Ratio	335,777	3.60	6.58	0.01	196.96

Table 14: Weekday Vs. Weekend

Dockless Bike Share (DBS)					
Week = 0 (Weekdays)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	61,889	15.21	15.71	0.02	120.00
Trip Distance	61,889	1.69	1.55	0.00	81.26
O-D Distance	61,889	0.98	0.80	0.00	23.28
Activity Ratio	59,271	2.81	8.11	0.00	360.20
Week = 1 (Weekend)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	31,005	19.87	19.24	0.03	120.00
Trip Distance	31,005	1.88	1.76	0.00	36.84
O-D Distance	31,005	0.94	0.80	0.00	11.23
Activity Ratio	29,155	3.54	10.02	0.00	432.82

Station Based Bike Share (SBBS)					
Week = 0 (Weekdays)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	108,536	12.83	16.16	2.00	120.00
Trip Distance	108,536	1.59	2.01	0.25	14.90
O-D Distance	108,536	0.57	0.43	0.00	5.13
Activity Ratio	100,043	2.50	4.53	0.46	161.62
Week = 1 (Weekend)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	41,138	19.76	20.99	2.00	120.00
Trip Distance	41,138	2.45	2.61	0.25	14.90
O-D Distance	41,138	0.64	0.56	0.00	4.53
Activity Ratio	35,431	3.52	6.58	0.49	145.23

Dockless Scooter Share (DSS)					
Week = 0 (Weekdays)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	1,471,405	9.51	10.15	0.22	120.00
Trip Distance	1,471,405	0.92	0.89	0.05	17.67
O-D Distance	1,471,405	0.50	0.48	0.00	15.11
Activity Ratio	1,396,018	2.78	5.13	0.01	211.13
Week = 1 (Weekend)					

Variable	Observations	Mean	Std. Dev.	Min	Max
Operational Time	658,891	13.56	13.30	0.20	120.00
Trip Distance	658,891	1.17	1.09	0.05	19.04
O-D Distance	658,891	0.54	0.52	0.00	15.06
Activity Ratio	617,102	3.69	6.76	0.01	221.09

Table 15: Peak Vs. Off Peak

Dockless Bike Share (DBS)					
Peak = 0 (Off peak)					
Variable	Observations	Mean	Std. Dev.	Min	Max
Operational Time	52,894	16.87	17.43	0.02	120.00
Trip Distance	52,894	1.74	1.66	0.00	81.26
O-D Distance	52,894	0.94	0.79	0.00	11.23
Activity Ratio	50,198	3.12	8.89	0.00	360.20
Peak = 1 (Morning peak)					
Variable	Observations	Mean	Std. Dev.	Min	Max
Operational Time	5,814	12.63	11.74	0.03	119.13
Trip Distance	5,814	1.74	1.41	0.00	17.28
O-D Distance	5,814	1.20	0.86	0.00	15.99
Activity Ratio	5,690	1.97	5.83	0.00	151.81
Peak = 2 (Midday peak)					
Variable	Observations	Mean	Std. Dev.	Min	Max
Operational Time	10,515	18.59	19.91	0.03	119.82
Trip Distance	10,515	1.81	1.78	0.00	29.80
O-D Distance	10,515	0.88	0.76	0.00	6.35
Activity Ratio	9,866	3.79	11.56	0.00	432.82
Peak = 3 (Afternoon peak)					
Variable	Observations	Mean	Std. Dev.	Min	Max
Operational Time	15,679	17.32	16.19	0.03	119.58
Trip Distance	15,679	1.84	1.55	0.00	23.24
O-D Distance	15,679	1.06	0.85	0.00	23.28
Activity Ratio	15,027	2.85	8.10	0.00	214.01
Peak = 4 (Evening peak)					
Variable	Observations	Mean	Std. Dev.	Min	Max
Operational Time	7,992	15.62	15.40	0.03	119.97
Trip Distance	7,992	1.62	1.45	0.00	24.97
O-D Distance	7,992	0.91	0.79	0.00	9.24
Activity Ratio	7,645	2.80	6.86	0.00	128.18

Station Based Bike Share (SBBS)					
Peak = 0 (Off peak)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	85,719	14.86	18.00	2.00	120.00
Trip Distance	85,719	1.84	2.23	0.25	14.90
O-D Distance	85,719	0.58	0.47	0.00	5.13
Activity Ratio	77,127	2.78	5.15	0.46	161.62
Peak = 1 (Morning peak)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	8,115	11.94	16.80	2.00	120.00
Trip Distance	8,115	1.48	2.09	0.25	14.90
O-D Distance	8,115	0.64	0.44	0.00	3.74
Activity Ratio	7,804	2.38	4.69	0.50	113.28
Peak = 2 (Midday peak)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	19,917	16.60	20.12	2.00	120.00
Trip Distance	19,917	2.06	2.50	0.25	14.90
O-D Distance	19,917	0.61	0.50	0.00	3.86
Activity Ratio	18,196	3.03	5.79	0.53	115.70
Peak = 3 (Afternoon peak)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	23,472	14.60	17.03	2.00	120.00
Trip Distance	23,472	1.81	2.11	0.25	14.90
O-D Distance	23,472	0.60	0.49	0.00	4.04
Activity Ratio	21,183	2.65	4.79	0.51	125.49
Peak = 4 (Evening peak)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	12,451	12.98	15.07	2.00	120.00
Trip Distance	12,451	1.61	1.87	0.25	14.90
O-D Distance	12,451	0.55	0.43	0.00	5.13
Activity Ratio	11,164	2.72	5.16	0.49	145.23

Dockless Scooter Share (DSS)					
Peak = 0 (Off peak)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	1,237,871	10.95	11.58	0.20	120.00
Trip Distance	1,237,871	1.00	0.97	0.05	19.04
O-D Distance	1,237,871	0.51	0.49	0.00	13.16
Activity Ratio	1,167,623	3.14	5.83	0.01	221.09
Peak = 1 (Morning peak)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**

Operational Time	111,051	7.06	7.27	0.28	120.00
Trip Distance	111,051	0.81	0.73	0.05	14.57
O-D Distance	111,051	0.53	0.47	0.00	15.06
Activity Ratio	106,639	2.19	3.65	0.02	211.13
Peak = 2 (Midday peak)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	308,236	10.30	11.31	0.22	120.00
Trip Distance	308,236	0.95	0.95	0.05	17.67
O-D Distance	308,236	0.48	0.46	0.00	14.51
Activity Ratio	291,533	3.01	5.50	0.02	180.00
Peak = 3 (Afternoon peak)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	364,646	11.66	11.74	0.23	119.95
Trip Distance	364,646	1.07	1.00	0.05	14.48
O-D Distance	364,646	0.54	0.53	0.00	13.47
Activity Ratio	343,857	3.23	5.99	0.02	189.23
Peak = 4 (Evening peak)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	108,492	10.68	10.48	0.22	118.80
Trip Distance	108,492	0.95	0.87	0.05	14.11
O-D Distance	108,492	0.55	0.51	0.00	15.11
Activity Ratio	103,468	2.64	5.26	0.02	142.06

Table 16: Seasonal Variation

Dockless Bike Share (DBS)					
Season = 1 (Early Spring)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	21,900	15.77	16.01	0.07	119.82
Trip Distance	21,900	1.69	1.52	0.00	18.12
O-D Distance	21,900	0.95	0.77	0.00	10.11
Activity Ratio	20,976	2.89	8.23	0.00	214.01
Season = 2 (Summer)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	16,603	19.57	18.83	0.03	119.82
Trip Distance	16,603	2.07	1.81	0.00	29.80
O-D Distance	16,603	1.02	0.83	0.00	9.92
Activity Ratio	15,717	4.06	12.06	0.03	432.82
Season = 3 (Fall)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	28,909	17.61	17.48	0.02	120.00

Trip Distance	28,909	1.81	1.70	0.00	81.26
O-D Distance	28,909	1.00	0.84	0.00	15.99
Activity Ratio	27,250	2.99	8.33	0.00	260.29
Season = 4 (Winter)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	25,482	14.84	16.08	0.02	120.00
Trip Distance	25,482	1.55	1.45	0.00	23.64
O-D Distance	25,482	0.91	0.77	0.00	23.28
Activity Ratio	24,483	2.60	7.05	0.00	256.52

Station Based Bike Share (SBBS)					
Season = 1 (Early Spring)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	18,709	17.67	20.17	2.00	120.00
Trip Distance	18,709	2.19	2.50	0.25	14.90
O-D Distance	18,709	0.67	0.56	0.00	5.13
Activity Ratio	16,357	2.78	5.23	0.46	113.28
Season = 2 (Summer)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	41,308	16.02	18.83	2.00	120.00
Trip Distance	41,308	1.99	2.34	0.25	14.90
O-D Distance	41,308	0.60	0.48	0.00	4.79
Activity Ratio	36,923	2.97	5.58	0.51	161.62
Season = 3 (Fall)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	59,912	12.55	15.66	2.00	120.00
Trip Distance	59,912	1.56	1.94	0.25	14.90
O-D Distance	59,912	0.55	0.42	0.00	3.86
Activity Ratio	55,547	2.59	4.64	0.49	132.66
Season = 4 (Winter)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	29,745	15.49	18.73	2.00	120.00
Trip Distance	29,745	1.92	2.33	0.25	14.90
O-D Distance	29,745	0.60	0.49	0.00	4.21
Activity Ratio	26,647	2.83	5.54	0.50	131.87

Dockless Scooter Share (DSS)					
Season = 1 (Early Spring)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**

Operational Time	614,213	10.44	10.84	0.20	120.00
Trip Distance	614,213	0.98	0.90	0.05	19.04
O-D Distance	614,213	0.59	0.52	0.00	15.11
Activity Ratio	593,015	2.38	4.76	0.01	174.69
Season = 2 (Summer)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	369,785	11.74	11.78	0.22	119.98
Trip Distance	369,785	1.09	1.00	0.05	16.67
O-D Distance	369,785	0.51	0.50	0.00	14.38
Activity Ratio	345,312	3.53	6.33	0.02	221.09
Season = 3 (Fall)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	577,396	10.30	10.98	0.20	120.00
Trip Distance	577,396	0.94	0.95	0.05	17.67
O-D Distance	577,396	0.45	0.45	0.00	14.51
Activity Ratio	541,122	3.25	5.59	0.01	211.13
Season = 4 (Winter)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	568,902	10.93	11.99	0.22	120.00
Trip Distance	568,902	1.00	0.99	0.05	17.15
O-D Distance	568,902	0.49	0.49	0.00	13.47
Activity Ratio	533,671	3.31	6.22	0.02	189.23

APPENDIX C (POST HOC BONFERRONI RESULTS FROM ANOVA TEST)

Table 17: Overall Sample for the Three Modes

Comparison of Operational Time by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	-2.0315	
P-value	0.0000	
DSS	-6.00612	-3.97462
P-value	0.0000	0.0000

Comparison of Trip Distance by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	0.074426	
P-value	0.0000	
DSS	-.761448	-.835874
P-value	0.0000	0.0000

Comparison of O-D Distance by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	-.376166	
P-value	0.0000	
DSS	-.452475	-.076309
P-value	0.0000	0.0000

Comparison of Activity Ratio by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	-.283345	
P-value	0.0000	
DSS	0.011229	0.294574
P-value	1.0000	0.0000

Table 18: Dockless Bike Share (DBS)

Comparison of Operational Time by Day of Week (Post hoc Bonferroni)						
Row Mean/ Col Mean	**0**	**1**	**2**	**3**	**4**	**5**
1	-4.18857					
P-value	0.0000					
2	-5.43195	-1.24338				

P-value	0.0000	0.0000				
3	-5.32513	-1.13656	0.106825			
P-value	0.0000	0.0000	1.0000			
4	-4.88744	-0.698872	0.54451	0.437685		
P-value	0.0000	0.0300	0.2590	0.9040		
5	-3.62799	0.560575	1.80396	1.69713	1.25945	
P-value	0.0000	0.1800	0.0000	0.0000	0.0000	
6	0.0145	4.20307	5.44645	5.33963	4.90194	3.64249
P-value	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Comparison of Trip Distance by Season (Post hoc Bonferroni)			
Row Mean/ Col Mean	**1**	**2**	**3**
2	0.383328		
P-value	0.0000		
3	0.119455	-0.263873	
P-value	0.0000	0.0000	
4	-0.141694	-0.525022	-0.26115
P-value	0.0000	0.0000	0.0000

Comparison of Trip Distance by Month (Post hoc Bonferroni)							
Row Mean/ Col Mean	**1**	**2**	**7**	**8**	**9**	**10**	**11**
2	-0.0548						
P-value	0.3560						
7	0.441692	0.496492					
P-value	0.0000	0.0000					
8	0.292668	0.347469	-0.149024				
P-value	0.0000	0.0000	0.0000				
9	0.09703	0.15183	-0.344663	-0.195639			
P-value	0.0000	0.0000	0.0000	0.0000			
10	0.082843	0.137643	-0.358849	-0.209826	-0.014187		
P-value	0.0020	0.0000	0.0000	0.0000	1.0000		
11	-0.182956	-0.128156	-0.624648	-0.475624	-0.279985	-0.265799	
P-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	
12	-0.126147	-0.071346	-0.567839	-0.418815	-0.223176	-0.208989	0.056809
P-value	0.0000	0.2860	0.0000	0.0000	0.0000	0.0000	0.8420

Comparison of O-D Distance by Peak (Post hoc Bonferroni)				
Row Mean/ Col Mean	**0**	**1**	**2**	**3**
1	0.258579			
P-value	0.0000			
2	-0.054115	-0.312694		
P-value	0.0000	0.0000		
3	0.119745	-0.138834	0.17386	
P-value	0.0000	0.0000	0.0000	
4	-0.026465	-0.285044	0.02765	-0.14621
P-value	0.0590	0.0000	0.1990	0.0000

Comparison of Activity Ratio by Weekday vs. Weekend (Post hoc Bonferroni)	
Row Mean/ Col Mean	**0**
1	0.731771
P-value	0.0000

Table 19: Station Based Bike Share (SBBS)

Comparison of Operational Time by Day of Week (Post hoc Bonferroni)						
Row Mean/ Col Mean	**0**	**1**	**2**	**3**	**4**	**5**
1	-5.96843					
P-value	0.0000					
2	-7.23667	-1.26824				
P-value	0.0000	0.0000				
3	-7.35024	-1.38181	-0.113568			
P-value	0.0000	0.0000	1.0000			
4	-6.21124	-0.242809	1.02543	1.139		
P-value	0.0000	1.0000	0.0000	0.0000		
5	-3.84481	2.12361	3.39186	3.50542	2.36642	
P-value	0.0000	0.0000	0.0000	0.0000	0.0000	
6	1.57914	7.54757	8.81581	8.92938	7.79038	5.42396
P-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Comparison of Trip Distance by Season (Post hoc Bonferroni)			
Row Mean/ Col Mean	**1**	**2**	**3**
2	-0.204979		
P-value	0.0000		

3	-0.63585	-0.430871	
P-value	0.0000	0.0000	
4	-0.270998	-0.066019	0.364852
P-value	0.0000	0.0010	0.0000

Comparison of Trip Distance by Month (Post hoc Bonferroni)							
Row Mean/ Col Mean	**1**	**2**	**7**	**8**	**9**	**10**	**11**
2	-0.100525						
P-value	0.0530						
7	-0.149376	-0.048851					
P-value	0.0000	1.0000					
8	-0.361646	-0.261121	-0.21227				
P-value	0.0000	0.0000	0.0000				
9	-0.767662	-0.667137	-0.618285	-0.406015			
P-value	0.0000	0.0000	0.0000	0.0000			
10	-0.579868	-0.479343	-0.430492	-0.218222	0.187793		
P-value	0.0000	0.0000	0.0000	0.0000	0.0000		
11	-0.426955	-0.32643	-0.277579	-0.065309	0.340706	0.152913	
P-value	0.0000	0.0000	0.0000	0.0890	0.0000	0.0000	
12	-0.15071	-0.050185	-0.001334	0.210936	0.616951	0.429158	0.276245
P-value	0.0000	1.0000	1.0000	0.0000	0.0000	0.0000	0.0000

Comparison of O-D Distance by Peak (Post hoc Bonferroni)				
Row Mean/ Col Mean	**0**	**1**	**2**	**3**
1	0.057379			
P-value	0.0000			
2	0.03301	-0.024368		
P-value	0.0000	0.0010		
3	0.020792	-0.036586	-0.012218	
P-value	0.0000	0.0000	0.0730	
4	-0.036181	-0.093559	-0.069191	-0.056973
P-value	0.0000	0.0000	0.0000	0.0000

Comparison of Activity Ratio by Weekday vs. Weekend (Post hoc Bonferroni)	
Row Mean/ Col Mean	**0**
1	1.02195
P-value	0.0000

Table 20: Dockless Scooter Share (DSS)

Comparison of Operational Time by Day of Week (Post hoc Bonferroni)						
Row Mean/ Col Mean	**0**	**1**	**2**	**3**	**4**	**5**
1	-3.56437					
P-value	0.0000					
2	-4.61082	-1.04645				
P-value	0.0000	0.0000				
3	-4.90023	-1.33587	-0.289412			
P-value	0.0000	0.0000	0.0000			
4	-4.27408	-0.709714	0.33674	0.626152		
P-value	0.0000	0.0000	0.0000	0.0000		
5	-2.97711	0.587261	1.63372	1.92313	1.29697	
P-value	0.0000	0.0000	0.0000	0.0000	0.0000	
6	0.037931	3.6023	4.64875	4.93817	4.31201	3.01504
P-value	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Comparison of Trip Distance by Season (Post hoc Bonferroni)			
Row Mean/ Col Mean	**1**	**2**	**3**
2	0.104861		
P-value	0.0000		
3	-0.045318	-0.150179	
P-value	0.0000	0.0000	
4	0.013825	-0.091037	0.059143
P-value	0.0000	0.0000	0.0000

Comparison of Trip Distance by Month (Post hoc Bonferroni)							
Row Mean/ Col Mean	**1**	**2**	**7**	**8**	**9**	**10**	**11**
2	-0.100233						
P-value	0.0000						
7	0.09674	0.196973					
P-value	0.0000	0.0000					
8	0.030154	0.130387	-0.066586				
P-value	0.0000	0.0000	0.0000				
9	-0.09831	0.001923	-0.19505	-0.128464			
P-value	0.0000	1.0000	0.0000	0.0000			
10	-0.10319	-0.002957	-0.199929	-0.133343	-0.00488		
P-value	0.0000	1.0000	0.0000	0.0000	1.0000		
11	-0.05327	0.046963	-0.15001	-0.083424	0.04504	0.04992	
P-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	

12	-0.029175	0.071058	-0.125915	-0.059329	0.069135	0.074015	0.024095
P-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Comparison of O-D Distance by Peak (Post hoc Bonferroni)				
Row Mean/ Col Mean	**0**	**1**	**2**	**3**
1	0.019299			
P-value	0.0000			
2	-0.026499	-0.045798		
P-value	0.0000	0.0000		
3	0.031959	0.01266	0.058458	
P-value	0.0000	0.0000	0.0000	
4	0.041036	0.021737	0.067535	0.009077
P-value	0.0000	0.0000	0.0000	0.0000

Comparison of Activity Ratio by Weekday vs. Weekend (Post hoc Bonferroni)	
Row Mean/ Col Mean	**0**
1	0.912332
P-value	0.0000

Appendix D (Post Hoc Bonferroni Results from ANOVA Test to show Variation between Modes)

Weekday Vs. Weekend:

Table 21: Mode Comparison for Week = 0

Comparison of Operational Time (for Week =0) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	-2.38075	
P-value	0.0000	
DSS	-5.70567	-3.32492
P-value	0.0000	0.0000

Comparison of Trip Distance (for Week=0) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	-0.096813	
P-value	0.0000	
DSS	-0.774157	-0.677344
P-value	0.0000	0.0000

Comparison of O-D Distance (Week=0) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	-0.407642	
P-value	0.0000	
DSS	-0.474907	-0.067265
P-value	0.0000	0.0000

Comparison of Activity Ratio (Week=0) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	-0.309347	
P-value	0.0000	
DSS	-0.027165	0.282182
P-value	0.6480	0.0000

Table 22: Mode Comparison for Week = 1

Comparison of Operational Time (for Week =1) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	-0.111821	

P-value	0.8790	
DSS	-6.3086	-6.19678
P-value	0.0000	0.0000

Comparison of Trip Distance (for Week=1) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	0.568013	
P-value	0.0000	
DSS	-0.717638	-0.677344
P-value	0.0000	0.0000

Comparison of O-D Distance (Week=1) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	-0.301155	
P-value	0.0000	
DSS	-0.405346	-0.104192
P-value	0.0000	0.0000

Comparison of Activity Ratio (Week=1) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	-0.019167	
P-value	1.0000	
DSS	0.153396	0.172564
P-value	0.0010	0.0000

Peak Vs. Off-Peak:

Table 23: Mode Comparison for Peak =1

Comparison of Operational Time (for Peak = 1) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	-0.692265	
P-value	0.0000	
DSS	-5.57503	-4.88277
P-value	0.0000	0.0000

Comparison of Trip Distance (for Peak = 1) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	-0.253361	
P-value	0.0000	

DSS	-0.923336	-0.669975
P-value	0.0000	0.0000

Comparison of O-D Distance (for Peak = 1) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	-0.557129	
P-value	0.0000	
DSS	-0.668495	-0.111366
P-value	0.0000	0.0000

Comparison of Activity Ratio (for Peak = 1) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	0.409277	
P-value	0.0000	
DSS	0.224318	-0.184958
P-value	0.0000	0.0000

Table 24: Mode Comparison for Peak =2

Comparison of Operational Time (for Peak = 2) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	-1.99407	
P-value	0.0000	
DSS	-8.28829	-6.29422
P-value	0.0000	0.0000

Comparison of Trip Distance (for Peak = 2) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	0.248324	
P-value	0.0000	
DSS	-0.865044	-1.11337
P-value	0.0000	0.0000

Comparison of O-D Distance (for Peak = 2) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	-0.268803	
P-value	0.0000	
DSS	-0.401598	-0.132795
P-value	0.0000	0.0000

Comparison of Activity Ratio (for Peak = 2) by Mode (Post hoc Bonferroni)

Row Mean/Col Mean	DBS	SBBS
SBBS	-0.755775	
P-value	0.0000	
DSS	-0.774107	-0.018333
P-value	0.0000	1.0000

Table 25: Mode Comparison for Peak =3

Comparison of Operational Time (for Peak = 3) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	-2.72194	
P-value	0.0000	
DSS	-5.66175	-2.93982
P-value	0.0000	0.0000

Comparison of Trip Distance (for Peak = 3) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	-0.032244	
P-value	0.0160	
DSS	-0.776273	-0.744028
P-value	0.0000	0.0000

Comparison of O-D Distance (for Peak = 3) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	-0.454881	
P-value	0.0000	
DSS	-0.517001	-0.06212
P-value	0.0000	0.0000

Comparison of Activity Ratio (for Peak = 3) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	-0.196418	
P-value	0.0070	
DSS	0.384035	0.580453
P-value	0.0000	0.0000

Table 26: Mode Comparison for Peak =4

Comparison of Operational Time (for Peak = 4) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	-2.633	
P-value	0.0000	
DSS	-4.93294	-2.29995
P-value	0.0000	0.0000

Comparison of Trip Distance (for Peak = 4) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	-0.004007	
P-value	1.0000	
DSS	-0.668209	-0.664203
P-value	0.0000	0.0000

Comparison of O-D Distance (for Peak = 4) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	-0.365644	
P-value	0.0000	
DSS	-0.361714	0.00393
P-value	0.0000	1.0000

Comparison of Activity Ratio (for Peak = 4) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	-0.083515	
P-value	0.8830	
DSS	-0.162161	-0.078646
P-value	0.0320	0.4230

Table 27: Mode Comparison for Peak =0

Comparison of Operational Time (for Peak = 0) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	-2.00904	
P-value	0.0000	
DSS	-5.91912	-3.91008
P-value	0.0000	0.0000

Comparison of Trip Distance (for Peak = 0) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	0.104651	
P-value	0.0000	

DSS	-0.736853	-0.841505
P-value	0.0000	0.0000

Comparison of O-D Distance (for Peak = 0) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	-0.355929	
P-value	0.0000	
DSS	-0.429215	-0.073286
P-value	0.0000	0.0000

Comparison of Activity Ratio (for Peak = 0) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	-0.3438	
P-value	0.0000	
DSS	0.013678	0.357478
P-value	1.0000	0.0000

Seasonal Variation:

Table 28: Mode Comparison for Season=1

Comparison of Operational Time (for Season =1) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	1.90658	
P-value	0.0000	
DSS	-5.3239	-7.23048
P-value	0.0000	0.0000

Comparison of Trip Distance (for Season = 1) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	0.506192	
P-value	0.0000	
DSS	-0.704241	-1.21043
P-value	0.0000	0.0000

Comparison of O-D Distance (for Season = 1) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**

SBBS	-0.278165	
P-value	0.0000	
DSS	-0.356645	-0.07848
P-value	0.0000	0.0000

Comparison of Activity Ratio (for Season = 1) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	-0.113814	
P-value	0.0800	
DSS	-0.507799	-0.393984
P-value	0.6480	0.0000

Table 29: Mode Comparison for Season=2

Comparison of Operational Time (for Season =2) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	-3.55074	
P-value	0.0000	
DSS	-7.83081	-4.28007
P-value	0.0000	0.0000

Comparison of Trip Distance (for Season = 2) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	-0.082115	
P-value	0.0000	
DSS	-0.982707	-0.900593
P-value	0.0000	0.0000

Comparison of O-D Distance (for Season = 2) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	-0.421303	
P-value	0.0000	
DSS	-0.512711	-0.091408
P-value	0.0000	0.0000

Comparison of Activity Ratio (for Season = 2) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	-1.0853	
P-value	0.0000	
DSS	-0.532785	0.552519
P-value	0.0000	0.0000

Table 30: Mode Comparison for Season=3

Comparison of Operational Time (for Season =3) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	-5.05363	
P-value	0.0000	
DSS	-7.30589	-2.25226
P-value	0.0000	0.0000

Comparison of Trip Distance (for Season = 3) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	-0.249114	
P-value	0.0000	
DSS	-0.869014	-0.6199
P-value	0.0000	0.0000

Comparison of O-D Distance (for Season = 3) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	-0.446518	
P-value	0.0000	
DSS	-0.546558	-0.10004
P-value	0.0000	0.0000

Comparison of Activity Ratio (for Season = 3) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	-0.399712	
P-value	0.0000	
DSS	0.267872	0.667585
P-value	0.0000	0.0000

Table 31: Mode Comparison for Season=4

Comparison of Operational Time (for Season =4) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	0.649552	
P-value	0.0000	
DSS	-3.91274	-4.56229
P-value	0.0000	0.0000

Comparison of Trip Distance (for Season = 4) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	0.376888	

P-value	0.0000	
DSS	-0.548722	-0.92561
P-value	0.0000	0.0000

Comparison of O-D Distance (for Season = 4) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	-0.307666	
P-value	0.0000	
DSS	-0.413162	-0.105495
P-value	0.0000	0.0000

Comparison of Activity Ratio (for Season = 4) by Mode (Post hoc Bonferroni)		
Row Mean/Col Mean	**DBS**	**SBBS**
SBBS	0.234674	
P-value	0.0000	
DSS	0.707978	0.473304
P-value	0.0010	0.0000

APPENDIX E (DESCRIPTIVE STATISTICS FOR COMPARING THE TWO MICROMOBILITY MODES)

Table 32: Day of the Week

Dockless Bikes Share (DBS)					
Day of Week = 0 (Sunday)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	14,675	23.12	43.74	0.07	1272.47
Trip Distance	14,675	1.99	2.11	0.00	77.80
O-D Distance	14,675	0.94	0.81	0.00	9.92
Activity Ratio	13,808	3.89	11.17	0.00	432.82
Day of Week = 1 (Monday)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	11,311	18.19	34.27	0.02	1049.02
Trip Distance	11,311	1.79	1.92	0.00	81.26
O-D Distance	11,311	0.96	0.79	0.00	10.11
Activity Ratio	10,838	3.33	10.56	0.00	360.20
Day of Week = 2 (Tuesday)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	11,579	15.89	26.65	0.02	709.98
Trip Distance	11,579	1.69	1.61	0.00	24.86
O-D Distance	11,579	0.98	0.82	0.00	15.99
Activity Ratio	11,068	2.85	8.67	0.00	214.01
Day of Week = 3 (Wednesday)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	11,901	17.94	47.18	0.03	1427.90
Trip Distance	11,901	1.73	1.79	0.00	72.88
O-D Distance	11,901	0.99	0.82	0.00	9.09
Activity Ratio	11,389	2.71	7.30	0.00	164.86
Day of Week = 4 (Thursday)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	13,000	17.46	36.48	0.05	1339.23
Trip Distance	13,000	1.74	1.84	0.00	82.68
O-D Distance	13,000	0.97	0.77	0.00	8.11
Activity Ratio	12,452	3.02	9.31	0.00	203.81
Day of Week = 5 (Friday)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	14,711	18.34	33.09	0.03	1289.62
Trip Distance	14,711	1.78	1.82	0.00	67.97
O-D Distance	14,711	0.99	0.83	0.00	23.28

Activity Ratio	14,064	2.98	8.87	0.00	256.52
Day of Week = 6 (Saturday)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	16,766	23.38	44.83	0.03	1359.28
Trip Distance	16,766	1.96	2.40	0.00	155.14
O-D Distance	16,766	0.94	0.82	0.00	13.99
Activity Ratio	15,752	3.73	17.00	0.00	1699.96

Station Based Bike Share (SBBS)					
Day of Week = 0 (Sunday)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	20,092	36.83	109.84	2.00	1404.00
Trip Distance	20,092	4.57	13.64	0.25	174.31
O-D Distance	20,092	0.62	0.56	0.00	4.53
Activity Ratio	17,199	7.88	33.09	0.49	857.06
Day of Week = 1 (Monday)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	21,560	24.74	92.53	2.00	1428.00
Trip Distance	21,560	3.07	11.49	0.25	177.29
O-D Distance	21,560	0.57	0.44	0.00	4.53
Activity Ratio	19,775	5.58	30.16	0.54	1268.44
Day of Week = 2 (Tuesday)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	21,499	22.39	88.11	2.00	1358.00
Trip Distance	21,499	2.78	10.94	0.25	168.60
O-D Distance	21,499	0.55	0.40	0.00	5.13
Activity Ratio	19,828	4.98	25.10	0.46	831.98
Day of Week = 3 (Wednesday)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	21,463	21.20	81.99	2.00	1424.00
Trip Distance	21,463	2.63	10.18	0.25	176.79
O-D Distance	21,463	0.56	0.42	0.00	4.79
Activity Ratio	19,898	4.56	22.51	0.52	961.75
Day of Week = 4 (Thursday)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	22,970	19.05	64.90	2.00	1422.00
Trip Distance	22,970	2.37	8.06	0.25	176.54
O-D Distance	22,970	0.57	0.43	0.00	5.13
Activity Ratio	21,079	3.90	19.78	0.50	1130.47
Day of Week = 5 (Friday)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**

Operational Time	23,398	25.10	84.15	2.00	1439.00
Trip Distance	23,398	3.12	10.45	0.25	178.65
O-D Distance	23,398	0.61	0.49	0.00	3.74
Activity Ratio	21,304	4.93	22.75	0.50	694.73
Day of Week = 6 (Saturday)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	22,815	38.74	114.69	2.00	1418.00
Trip Distance	22,815	4.81	14.24	0.25	176.04
O-D Distance	22,815	0.65	0.57	0.00	3.86
Activity Ratio	19,536	8.14	36.35	0.53	1542.82

Table 33: Weekday Vs. Weekend

Dockless Bikes Share (DBS)					
Week = 0 (Weekdays)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	62,502	17.60	36.10	0.02	1427.90
Trip Distance	62,502	1.75	1.80	0.00	82.68
O-D Distance	62,502	0.98	0.81	0.00	23.28
Activity Ratio	59,811	2.98	8.99	0.00	360.20
Week= 1 (Weekend)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	31,441	23.26	44.32	0.03	1359.28
Trip Distance	31,441	1.98	2.27	0.00	155.14
O-D Distance	31,441	0.94	0.81	0.00	13.99
Activity Ratio	29,560	3.80	14.57	0.00	1699.96

Station Based Bike Share (SBBS)					
Week = 0 (Weekdays)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	110,890	22.50	82.72	2.00	1439.00
Trip Distance	110,890	2.79	10.27	0.25	178.65
O-D Distance	110,890	0.57	0.44	0.00	5.13
Activity Ratio	101,884	4.78	24.24	0.46	1268.44
Week= 1 (Weekend)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	42,907	37.84	112.45	2.00	1418.00
Trip Distance	42,907	4.70	13.96	0.25	176.04
O-D Distance	42,907	0.64	0.56	0.00	4.53
Activity Ratio	36,735	8.02	34.86	0.49	1542.82

Table 34: Peak Vs. Off Peak

Dockless Bikes Share (DBS)					
Peak = 0 (Off peak)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	53,501	19.83	42.11	0.02	1427.90
Trip Distance	53,501	1.81	2.09	0.00	155.14
O-D Distance	53,501	0.94	0.80	0.00	13.99
Activity Ratio	50,755	3.33	12.23	0.00	1699.96
Peak = 1 (Morning peak)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	5,846	14.15	27.49	0.03	913.70
Trip Distance	5,846	1.77	1.55	0.00	26.20
O-D Distance	5,846	1.20	0.87	0.00	15.99
Activity Ratio	5,718	2.03	6.04	0.00	151.81
Peak = 2 (Midday peak)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	10,703	21.74	36.22	0.03	1293.92
Trip Distance	10,703	1.91	2.04	0.00	29.80
O-D Distance	10,703	0.88	0.76	0.00	6.35
Activity Ratio	10,036	4.18	12.94	0.00	432.82
Peak = 3 (Afternoon peak)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	15,831	19.48	32.76	0.03	1339.23
Trip Distance	15,831	1.90	1.84	0.00	82.68
O-D Distance	15,831	1.06	0.86	0.00	23.28
Activity Ratio	15,152	2.97	8.63	0.00	236.30
Peak = 4 (Evening peak)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	8,062	18.17	40.64	0.03	1154.52
Trip Distance	8,062	1.66	1.58	0.00	24.97
O-D Distance	8,062	0.91	0.79	0.00	9.24
Activity Ratio	7,710	2.98	8.01	0.00	215.65

Station Based Bike Share (SBBS)					
Peak = 0 (Off peak)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	88,319	28.42	97.34	2.00	1439.00
Trip Distance	88,319	3.53	12.08	0.25	178.65
O-D Distance	88,319	0.58	0.48	0.00	5.13
Activity Ratio	79,129	6.10	30.26	0.46	1542.82
Peak = 1 (Morning peak)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	8,272	16.11	42.93	2.00	1404.00

Trip Distance	8,272	2.00	5.33	0.25	174.31
O-D Distance	8,272	0.64	0.44	0.00	3.74
Activity Ratio	7,934	3.31	13.63	0.50	781.96
Peak = 2 (Midday peak)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	20,346	21.42	50.94	2.00	1425.00
Trip Distance	20,346	2.66	6.32	0.25	176.91
O-D Distance	20,346	0.61	0.50	0.00	3.86
Activity Ratio	18,447	3.78	11.10	0.53	445.45
Peak = 3 (Afternoon peak)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	23,981	26.16	99.50	2.00	1307.00
Trip Distance	23,981	3.25	12.35	0.25	162.26
O-D Distance	23,981	0.60	0.49	0.00	4.04
Activity Ratio	21,578	5.35	27.67	0.51	1130.47
Peak = 4 (Evening peak)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	12,879	32.02	112.93	2.00	1393.00
Trip Distance	12,879	3.98	14.02	0.25	172.94
O-D Distance	12,879	0.55	0.43	0.00	5.13
Activity Ratio	11,531	7.57	32.14	0.49	653.07

Table 35: Seasonal Variation

Dockless Bikes Share (DBS)					
Season = 1 (Early Spring)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	22,106	17.54	25.93	0.07	667.22
Trip Distance	22,106	1.74	1.69	0.00	24.86
O-D Distance	22,106	0.95	0.78	0.00	10.11
Activity Ratio	21,170	3.04	8.97	0.00	301.83
Season = 2 (Summer)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	16,825	22.77	43.98	0.03	1427.90
Trip Distance	16,825	2.17	2.38	0.00	155.14
O-D Distance	16,825	1.02	0.84	0.00	9.92
Activity Ratio	15,910	4.46	18.84	0.00	1699.96
Season = 3 (Fall)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	29,270	20.79	41.70	0.02	1339.23
Trip Distance	29,270	1.89	2.08	0.00	82.68

O-D Distance	29,270	1.00	0.84	0.00	15.99
Activity Ratio	27,579	3.20	9.27	0.00	260.29
Season = 4 (Winter)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	25,742	17.56	41.90	0.02	1289.62
Trip Distance	25,742	1.60	1.74	0.00	77.80
O-D Distance	25,742	0.91	0.78	0.00	23.28
Activity Ratio	24,712	2.71	7.45	0.00	256.52

Station Based Bike Share (SBBS)					
Season = 1 (Early Spring)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	19,517	41.44	140.39	2.00	1439.00
Trip Distance	19,517	5.15	17.43	0.25	178.65
O-D Distance	19,517	0.67	0.57	0.00	5.13
Activity Ratio	16,987	8.66	41.64	0.46	961.75
Season = 2 (Summer)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	42,294	23.97	67.49	2.00	1410.00
Trip Distance	42,294	2.98	8.38	0.25	175.05
O-D Distance	42,294	0.60	0.49	0.00	4.79
Activity Ratio	37,606	4.88	22.52	0.51	1268.44
Season = 3 (Fall)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	61,194	21.30	75.19	2.00	1424.00
Trip Distance	61,194	2.64	9.33	0.25	176.79
O-D Distance	61,194	0.56	0.43	0.00	3.86
Activity Ratio	56,557	4.54	20.39	0.49	786.06
Season = 4 (Winter)					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operational Time	30,792	32.23	110.81	2.00	1409.00
Trip Distance	30,792	4.00	13.76	0.25	174.93
O-D Distance	30,792	0.60	0.49	0.00	4.21
Activity Ratio	27,469	7.06	34.38	0.50	1542.82

APPENDIX F (RESULTS FROM TWO SAMPLE T-TEST OF MEANS)

Weekday Vs. Weekend:

Table 36: Mode Comparison for Week=0

Comparison of Operational Time (for Week =0) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	-14.06621381
P-value	6.48541E-45

Comparison of Trip Distance (for Week=0) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	-25.20416154
P-value	6.4554E-140

Comparison of O-D Distance (Week=0) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	135.9988667
P-value	0

Comparison of Activity Ratio (Week=0) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	-17.51959485
P-value	1.17558E-68

Table 37: Mode Comparison for Week=1

Comparison of Operational Time (for Week =1) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	-21.78996247
P-value	6.1651E-105

Comparison of Trip Distance (for Week=1) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	-34.2497036
P-value	4.3259E-255

Comparison of O-D Distance (Week=1) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	60.74552369
P-value	0

Comparison of Activity Ratio (Week=1) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	-19.48365603
P-value	2.60378E-84

Peak Vs. Off Peak:

Table 38: Mode Comparison for Peak = 1

Comparison of Operational Time (for Peak = 1) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	-3.080715454
P-value	0.00206901

Comparison of Trip Distance (for Peak = 1) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	-3.208302442
P-value	0.001338191

Comparison of O-D Distance (for Peak = 1) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	50.05975053
P-value	0

Comparison of Activity Ratio (for Peak = 1) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	-6.687987681
P-value	2.35067E-11

Table 39: Mode Comparison for Peak = 2

Comparison of Operational Time (for Peak = 2) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	0.580515768
P-value	0.56157107

Comparison of Trip Distance (for Peak = 2) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	-11.85172815
P-value	2.47533E-32

Comparison of O-D Distance (for Peak = 2) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	37.35851529
P-value	7.7567E-299

Comparison of Activity Ratio (for Peak = 2) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	2.766257688
P-value	0.005674025

Table 40: Mode Comparison for Peak = 3

Comparison of Operational Time (for Peak = 3) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	-8.16551625
P-value	3.29388E-16

Comparison of Trip Distance (for Peak = 3) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	-13.6042971
P-value	4.6897E-42

Comparison of O-D Distance (for Peak = 3) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	67.32699253
P-value	0

Comparison of Activity Ratio (for Peak = 3) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	-10.26154302
P-value	1.13393E-24

Table 41: Mode Comparison for Peak = 4

Comparison of Operational Time (for Peak = 4) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	-10.59589289
P-value	3.62695E-26

Comparison of Trip Distance (for Peak = 4) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	-14.79257782

P-value	2.90077E-49

Comparison of O-D Distance (for Peak = 4) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	42.99952565
P-value	0

Comparison of Activity Ratio (for Peak = 4) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	-12.27516814
P-value	1.65782E-34

Table 42: Mode Comparison for Peak = 0

Comparison of Operational Time (for Peak = 0) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	-19.325836
P-value	4.1682E-83

Comparison of Trip Distance (for Peak = 0) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	-32.49192216
P-value	9.8326E-231

Comparison of O-D Distance (for Peak = 0) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	105.9449506
P-value	0

Comparison of Activity Ratio (for Peak = 0) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	-19.67503502
P-value	4.71364E-86

Seasonal Variation:

Table 43: Mode Comparison for Season = 1

Comparison of Operational Time (for Season =1) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	-24.84267179
P-value	3.0121E-135

Comparison of Trip Distance (for Season = 1) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	-28.87918551
P-value	1.3594E-181

Comparison of O-D Distance (for Season = 1) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	41.97418624
P-value	0

Comparison of Activity Ratio (for Season = 1) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	-19.08353785
P-value	8.24495E-81

Table 44: Mode Comparison for Season = 2

Comparison of Operational Time (for Season =2) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	-2.119869579
P-value	0.0340212

Comparison of Trip Distance (for Season = 2) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	-12.29583411
P-value	1.05162E-34

Comparison of O-D Distance (for Season = 2) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	76.19144113
P-value	0

Comparison of Activity Ratio (for Season = 2) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	-2.09440467
P-value	0.036228638

Table 45: Mode Comparison for Season = 3

Comparison of Operational Time (for Season =3) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	-1.093254582
P-value	0.274284949

Comparison of Trip Distance (for Season = 3) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	-13.74191777
P-value	6.2902E-43

Comparison of O-D Distance (for Season = 3) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	105.5238409
P-value	0

Comparison of Activity Ratio (for Season = 3) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	-10.47589317
P-value	1.15614E-25

Table 46: Mode Comparison for Season =4

Comparison of Operational Time (for Season =4) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	-20.07637069
P-value	2.43641E-89

Comparison of Trip Distance (for Season = 4) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	-27.80446382
P-value	5.2935E-169

Comparison of O-D Distance (for Season = 4) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	57.61431034
P-value	0

Comparison of Activity Ratio (for Season = 4) by Mode (Two Tailed T-Test)	
Row Mean/Col Mean	**DBS**
SBBS	-19.51003307
P-value	1.80684E-84

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Vita

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